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> Internet in schools. The effect on educational performance Peru: 2007-2011

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Overview

This paper looks at the effect of Internet access and broadband Internet access on the educational performance of second-grade students in Peru. According to the literature, access and the properly guided use of information technologies (ICT) at such a young age have an effect on reading comprehension skills and the development of mathematical reasoning. In particular, Internet access has an impact on multiple cognitive skills such as information processing, language development and visual intelligence, as well as meta-cognitive skills like planning, search strategies and the evaluation of information.

The period of analysis covers the years 2007-2011. As an identification strategy, special emphasis was placed on characterizing the potential dynamic of Internet access and access to high-speed Internet in schools. The analysis methodology consists of quasi-experimental impact evaluation techniques (Difference-in-Differences and pairing) controlling for observable and unobservable variables. The main databases used are the School Census 2007-2011 (CE for its acronym in Spanish), the School Census Evaluation (ECE for its acronym in Spanish) 2007-2011 and the Huascaran-Digete Program's database.

The findings reveal that the introduction of information and communication technologies (ICT) like Internet, in schools is associated with no or positive impacts on performance, measured as a percentage of students achieving a satisfactory level of educational attainment (level 2).

The most significant impacts are found in the ECE's 2011 results, more so in reading comprehension than in logical-mathematical reasoning. The results of the different methods used to measure the evaluated impact suggest that there is a "year effect" in 2011. Moreover, the effect after one year of Internet access is between 0 and 2.9 in the percentage of students achieving a satisfactory level in logical-mathematical reasoning and between 5.2 and 6.9% in reading comprehension.

The impact of access to high-speed Internet in schools on performance in 2011 was also estimated. Only one of the 16 estimators calculated was significant controlling for observable variables, but a 15% statistical significance. That is to say, access to high speed Internet does not seem to have a significant effect on educational performance measured as the percentage of students that achieves a satisfactory level of knowledge.

1. Introduction[1]

The prolific empirical literature highlights the role of education in various aspects such as human capital formation, opportunities to enter the job market and productivity improvements in the economy (Glewwe, Kremer, Moulin and Itzewitz, 2004). Unfortunately, various international assessments find that the widespread dissemination of basic education in developing countries has coincided with (or caused) a supply of poor quality services (Banerjee and Duflo, 2011; Organization for Economic Cooperation and Development, 2010, among others) with consequences in educational achievement on standardized tests such as PISA,[2] which is why many countries have been adopting policies for universal quality education. In particular, it highlights the enthusiasm among policy makers and international agencies in regard to the role of information and communication technologies (ICT)[3] for this objective.

The literature addressing the pedagogical use of ICT and its effect on the quality of education has emphasized its potential effect on the students' cognitive development and the development of computer skills per se (Johnson, 2006). According to this line of argument, the use of ICT for educational purposes improves students' memory and attention processes by increasing the effectiveness of the teaching-learning process by shifting from a teacher-based model to a student-based one

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1 The author would like to thank Juan León (GRADE), Carmen Montero (IEP) y José S. Rodríguez (PUCP)for their excellent feedback and suggestions.
2 According to the results of PISA 2009, the proportion of low-performing students (those who do not reach a minimum level of achievement) in Latin American countries was 58% of students in mathematics, 45% in reading and 48% in science, while the average for students in OECD countries was 20% (Ministry of Education of Spain, 2010).
3 ICT consists of hardware, software, networks and media for collecting, storing, processing, transmiting and presenting information (voice, data, text and images) (World Bank, 2002).

(Trucano, 2005 and Johnson, 2006). In parallel, its insertion in schools reduces differences of opportunity between people with and those without access to new technologies, defined as the digital divide (Sunkel, 2006; Judge, Puckett, and Bell, 2006).

However, recently it has been questioned whether ICT could impair education quality if they are incorporated in a disjointed manner, if the teacher does not have the human capital to properly use them; if students cannot appropriate these technologies and effectively use them to improve their learning; or if the availability of educational applications and infrastructure does not support its widespread dissemination. These risks are not insignificant, considering that the high costs of entry (i.e., investment in infrastructure) and maintenance of these interventions, in addition to their rapid technological expiry, can render them costly alternatives.

Empirical evidence of a causal effect offers inconclusive results that are specific to the type of technology and form of insertion in educational practice (Claro, 2010; Trucano, 2005; Lee & O'Rourke, 2006; Jackson et al, 2006; among others). While computer-aid instruction (CAI) programs have recently received special attention in the literature reporting positive effect results (IDB, 2011; Barrow, Markan and Rose, 2009 and Linden, L., A. Banerjee and E. Duflo, 2003), empirical research has focused on the role of the computer, and found mixed evidence of the impact. On this point, there is a surprising lack of empirical evidence for developing countries on phenomena that have revolutionized the economic and social life of the population, including access to broadband (high speed Internet) and mobile telephony, topics worked only tangentially in some studies (Toyama, 2010). So, there is still a long way to go to unravel this relationship, which has yet to be explored in local literature.

In this area, an important issue to consider is the fact that a clear identification of the impact of ICT in schools could face significant methodological questioning associated with potential problems of selection bias (presence of omitted variables and reverse causality problems), which reduce the credibility of the estimates. In this regard, recent evaluations with sophisticated experimental designs have made substantial progress to address these problems and improve our understanding of the impact of interest (Aker, Ksolly and Lybbert, 2012; Barrow, Richburg, Rouse and Brock, 2009; Cristiá, Ibarrarán, Cueto and Severin, 2011; Jackson, et al, 2006; Spiezia, 2010). However, the specificity and underpowered context often limit external validity of the results in many cases.

In this context, the main objective of the research is to approach from a quantitative perspective the causal relationship between the incorporation of ICTs and educational performance in Peru, as measured by indicators of educational achievement. More specifically, the effect of the advance of Internet connectivity in primary schools (public and private) on satisfactory student performance on students' standardized tests over the 2007-2011 analysis period will be econometrically explored, with special emphasis on the nature of the impact.

To do this, two census databased were used: CE (2007-2011) and the ECE (2007-2011), which include information on educational infrastructure and students' performance on standardized tests, among other variables: For this reason, two census databases will fail. An important advantage of these databases is that they collect information from almost every basic education institutions in the country, reducing the problems of external validity.

The impact is identified in two phases. First, the impact of Internet access (independent of the type of technology) is evaluated. Then, it is determined whether there are differences in the type of access technology (broadband) and the impact on educational performance.

To address the problems of endogeneity, a mixed econometric identification strategy based on the combination of the matching method through propensity score matching (PSM) and the Difference-in-Differences (DD) is proposed. The combined use of the two methods reduces the risk of obtaining biased estimates and increases the robustness of the estimates (Blundell and Costa Dias, 2000). The DD technique to control for unobservable fixed factors over time which could be correlated with the treatment and its combination with matching techniques seeks to improve the comparability between groups, controlling for heterogeneity in the baseline.

One limitation of this research is the lack of information indicating any Internet use by students and the link with educational performance indicators. In an ideal scenario, we would be able to obtain the following variables at the student level, breaking down use in school and in the home: time spent online (minutes/day), number of logins per day, number of domains visited per day and number of e-mails per day (Jackson, et.al., 2006). However, the research contributes to the local empirical literature by providing a first approximation to the effect of the progress of connectivity in schools in Peru.

The rest of this paper is structured as follows. In section 2 there is a brief review of the literature on the impact of ICT and the Internet on educational outcomes, followed by a presentation of the theoretical framework of the research. Section 3 explains the progress of Internet connectivity and educational performance in primary schools in Peru. Section 4 describes the databases used, and section 5 outlines the econometric methodology deployed. Sections 6 and 7 describe the strategy of identifying the impact of Internet access and the impact of broadband Internet access, respectively. Section 8 presents and discusses the results of both evaluations. Finally, Section 9 concludes with some final considerations regarding the implications of the findings.

2. BACKGROUND

In this section we discuss the theoretical framework that allows us to hypothesize about the direction of the impact which guides the interpretation of results. Also, a brief review of empirical literature is presented.

2.1 Theoretical framework

Conceptually speaking, this document falls within the extensive literature on the function of educational production and the controversy over the role of educational inputs (Glewwe, Kremer, Moulin and Zitzewitz, 2004; Hanushek and Lavy, 1993; Kremer, 2003; Kremer, Miguel and Thornton, 2009; Duflo, Glennerster and Kremer, 2008). Following this approach, the educational production function is defined as one that relates quantities of factors of production employed (inputs), given a state of technology with levels of product or results achieved (outputs).

Accordingly, the work of Glewwe, Kremer, Moulin and Zitzewitz (2004) presents a production function for learning that can be represented as a structural relationship as follows:

$$A = a(S, Q, C, H, \mathrm{I})$$

Where A is the skills learned (achievements), S is years of schooling, Q is a vector of characteristics related to the school and teacher (quality), C is a vector of the child's characteristics (including "innate ability"), H is a vector of household characteristics (i.e., parental preferences in terms of education, family size, spending power, credit restrictions, among other socioeconomic variables) and I is a vector of school inputs controlled by the parents and, therefore, are endogenous, such as the purchase of textbooks and other materials.[4]

The relationship suggested is considered structural because it holds (or remains unchanged) even though the agents involved (households or schools) modify their supply of inputs in the event of the exogenous provision of some other input of the production function (Duflo, Glennerster and Kremer, 2008). After this substitution of endogenous inputs, depending on the degree of complementarity or substitution between them, a function is obtained in its reduced form:

$$A = f(i, \mathrm{x})$$

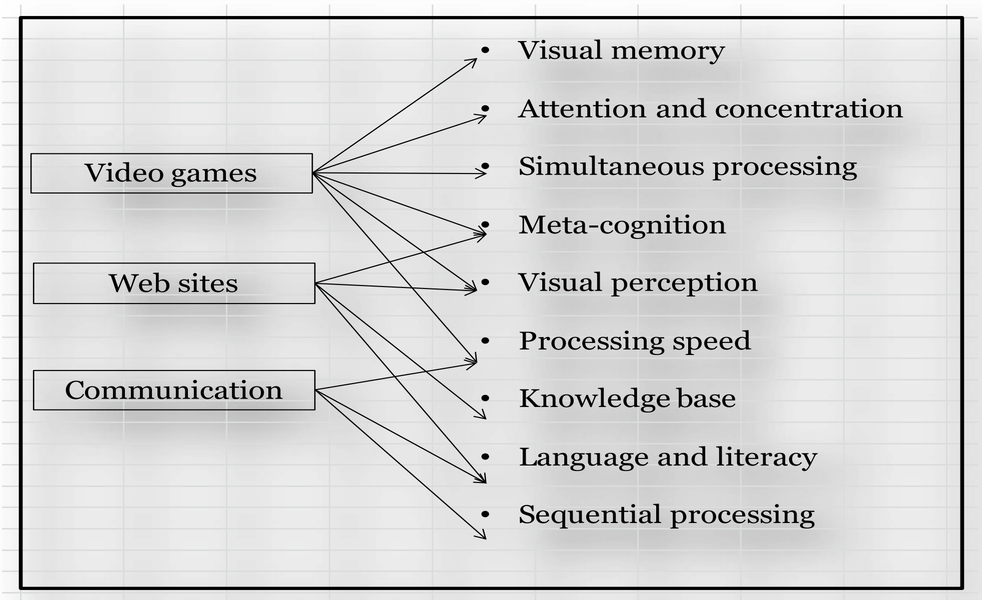
Where i denotes the input of interest (Internet access) and X, other educational inputs, which may include characteristics specific to the students or the school they attend. However, how does Internet access affect the educational performance of second-grade students seven to eight years of age?

According to the theoretical framework proposed by Johnson (2006)[5] summarized in Figure 1, the use of the Internet has a positive effect on the cognitive process. A review of the three main uses of the Internet makes it possible to identify the channels through which each

4 Prices are also related to education as they may include school fees, prices of school supplies purchased by parents, and even the wages paid for child labor. However, they are not considered in the equation because their effect works through decisions made by the endogenous variables S and I.

5 Johnson (2006) developed a theoretical framework based on the following theories of cognitive development: Cognitive Model of Information Processing, Sociocultural Perspective of Cognitive Development, Cognitive Processing Model of PASS (Planning, Attention-Arousal, Simultaneous and Successive) and Neurology of the Cognitive Process use has an impact on learning. The use of video games stimulates visual memory, capacity for concentration, and information processing and speed, visual perception and meta-cognitive skills or skills for knowing how and when to learn, such as planning and evaluating information, and problem solving. Access to web sites also has an impact on these meta-cognitive and visual perception skills because the user is required to deploy efficient learning strategies in the face of the entire universe of information, strategies related to the learning model of processing information, which consists of encouraging skills such as: selection, memory and interpretation of information. In addition, access to information on web sites amplifies the knowledge base and the use of language. Finally, the use of this resource as a communication tool (social networks) improves the speed and capacity successive information processing capacity and the development of language and literacy.

Figure 1 Theoretical framework regarding the effects of the Internet on cognitive processes



Source: Johnson (2006)

2.2 Evidence of the impact

Several authors argue that there is a positive effect of the insertion of new information and communication technologies (ICT) in education. Aker, J., and C. Ksolly and T. Lybbert (2012) report that the use of cell phones in Africa had a positive impact on access to public services such as education, with an impact on literacy levels. ICTs could also have positive effects on educational performance by increasing cognitive and meta-cognitive skills, as developed in the theoretical framework.

For the past decade, the empirical literature has focused on assessing the consequences of the use of computers on students' performance. At the level of developed countries, Spiezia (2010) performed a study on the effects of computer use (at school and/or home) on educational performance on the section of sciences (physics and chemistry) of the PISA 2006, controlling the selection bias of computer use at home with characteristics pertaining to the students and their households. The sample considers students from 33 countries, 26 OECD members and seven candidate countries. The results show a positive impact that is enhanced in those students who use a computer at home in addition to using one at school.

Furthermore, Peltenburg, den Heuvel and Doig (2009), focus on students between 8 and 12 years of age in two special schools in the Netherlands. The results show that the use of a computer and visual tools to explain math problems allows students to solve problems that they could not do through the traditional way of teaching.

Ramon and Murillo (2012) found, based on a sample of sixth-grade students from 16 countries in Latin America, that students who have access to a computer at home perform better on standardized tests. This effect is greater if there are more than 10 computers in the school they attend. Both effects occur despite controlling for socioeconomic variables. Similarly, Cristiá, J., A. Czerwonkoy and P. Garofalo (2010) evaluated an IDB project to provide public schools in Peru with electricity and 10 computers each. The project, part of the Huascarán program, also prioritized Internet access to these schools. In addition to being public institutions, the schools selected had the highest enrollment rate, a committed teaching staff (including the principal and teachers), and the easiest access. The study found a statistically zero impact on the repetition, dropout and enrollment rates. Variables related to educational performance were not considered.

Lee and O'Rourke (2006) performed a qualitative analysis of the effect of the use of computers (hardware) and educational programs (software) provided by IBM for the KidSmart Early Learning program among children between four and five years of age in Western Australia. The program offered one computer for every two students. We conclude that these elements are a tool to improve literacy through traditional teaching techniques, as well as a tool for fostering collaborative behavior in children by generating problem-solving conversations ("try this or otherwise this"), and planning and organizational language. Likewise, they assist in the development of multiple literacy levels, as is the case for students who require more visual learning techniques.

In regard to the software used, Lee and O'Rourke (2006) note that some Australian cultural references were outdated and were used as examples that computers will not always be right and that they students need to constantly question the information that computers provide them. This is linked to another finding of the study concerning the consolidation of prior knowledge based on the information provided by the software. Without proper teacher training, teachers can use the computer as simply an additional tool of the curriculum with learning to use it as the end result in itself. However, teachers that received training displayed a more comprehensive use which involved changes in how students learned and what they learned.

In Peru, the program One Laptop per Child (OLPC) has produced valuable results. This program is delivering XO-1 laptops with learning software to public school students between 6 and 12 years of age in Peru. However, as Villanueva-Mansilla and Olivera (2012) point out, all innovation faces institutional barriers. The ideal of the program was to generate collective learning among teachers, principals and students. However, from the beginning, participation from teachers and the educational system in general was declined; as a result, the initiative was received with suspicion by many of the people involved in education.

"While the interviews showed that principals, teachers and students perceive the XO-1 as a positive tool for school, the lack of training appeared as the greatest barrier" (Villanueva-Mansilla and Olivera 2012, p.198).

Also, the expectation for the XO-1 was that it would allow users to learn how to use a computer rather than act as a learning tool. For this reason, a limited and exclusive use was made of it during computer class. Moreover, some teachers felt that they should be used only by students in the early elementary grades and that older students should use computers with Windows operating system because the job market demands it. These problems are closely linked to the lack of inclusion of teachers and principals in the program.

Cristiá, Cueto, Ibarrarán, Santiago and Severin (2011) evaluated the effects of the OLPC program. The study found no effect on enrollment or standardized tests or Logical-Mathematical reasoning or Reading Comprehension. However, positive results were found in general cognitive skill tests that measure nonverbal abstract reasoning; verbal fluency tests that capture language functions; and encoding tests that measure students' processing speed and memory capacity. We believe that in order to achieve a positive impact in reading comprehension and logical-mathematical reasoning, the use of the XO-1 requires a high quality guide which would involve greater ties with teachers in the program through better training. This coincides with the findings of Lee and O'Rourke (2006) presented above in the case of the KidSmart Early Learning Program in Australia, which showed that teachers with the right training showed full use of computers as a supplement to traditional techniques.

With regard to the effects on the use of the Internet, Sprietsma (2007) evaluated the effect of the availability of a computer lab at school and the use of computers and the Internet for educational purposes in standardized test performance among students in 4th grade (10 years old), 8th grade (14 years old) and 11th grade (16-17 years old). The methodology involves the construction of a pseudo panel as introduced by Deaton with three cuts: 1999, 2011 and 2003. It was found that the presence of computer labs has negative effects on reading comprehension and, in particular, logical-mathematical reasoning. One hypothesis is that these negative effects are due to a trade-off between investing in computer labs versus other teaching methods. However, it is found that the use of the Internet by the teacher for educational purposes does have a positive impact on the results of both disciplines.

In terms of Internet access at home, Vigdor and Ladd (2010) assessed its effect on educational performance of students in South Carolina (USA), from 5th through 8th grade (10-14 years old). They find a significant and persistent negative impact on the results of logical-mathematical reasoning and reading comprehension. They argue that this may be due to an inefficient role played by parents to control their children's use of the Internet.

Along the same lines, Chandra and Loyd (2008) conducted an experiment with 15- and 16-year-old high school students in Australia enrolled in science courses (chemistry and physics). All students are taught the course in a traditional face-to-face format for the first year. In the second year, the students are divided into two groups, one takes a blended learning course, and the other just as the first year (face-to-face). There is a positive impact on students who took the blended course, although it is not a global impact because some students had difficulty adjusting to the new course dynamics.

Jackson, et. al. (2006) develop a longitudinal study of Michigan State University's project called HomeNetToo to provide Internet access to low-income children between 10 and 18 years of age (13.8 years old on average). The main hypothesis of the study is that increased use of the Internet at home is associated with better academic performance. Internet use was measured continuously for 16 months with indicators of online time (min/day), number of logins per day, domains visited per day and number of daily e-mails. Educational performance was measured based on the results of the GPA (Grade Point Averages) and the MEAP exam (Michigan Education Assessment Program) at the start of the evaluation, after six months and one year after exposure to the "treatment." Positive effects of Internet use on standardized tests were found after six months, one year and 16 months; no differentiated effects by age were found.

3. Progress of connectivity in schools and educational performance

In terms of the progress of Internet connectivity in schools, as of 2012, Peru is still lagging behind in relation to the international arena. Only 26.3% of primary schools and 49.6% of secondary schools are connected (see Table 1).[6] Despite this scenario, an increasing number of schools are opting to connect to the Internet. In the case of primary schools, the figure is eight times higher than in 2004. Nevertheless, a rhythm of differentiated adoption has characterized then increase in access when taking the school's geographical location into account, which could result in important repercussions in terms of equity.

Table 1. Percentage of primary and secondary schools with Internet Access, Peru: 2000-2012.

Year	Primary			Secondary		
	Total	Urban	Rural	Total	Urban	Rural
2000	1,6	5,4	0,1	8,3	12,6	0,5
2001	1,8	6	0,1	9,3	14,7	0,5
2002	2,6	7,4	0,3	11,3	16,1	2,1
2003	1,8	5,9	0	9,5	14,9	0,4
2004	3,3	10,1	0	16,8	25,4	1,2
2005	5,9	15,3	0,1	19,2	25,9	0,8
2006	10,7	31,8	0,9	31,9	48,2	5,9
2007	10,9	29,3	0,8	31,6	43,7	6,2
2008	11,8	31,3	1,7	32,8	45,4	9,3
2009	10,7	26,9	0,6	27,8	38,2	3,1
2010	16,3	40	1,2	41,9	56,7	6,4
2011	17,4	36,8	4,8	36,7	49,2	8,9
2012	26,3	54	8,5	49,6	65,5	14,8

Source: School Census, Ministry of Education-Unit of Educational Statistics. Retrieved from: <http://escale.minedu.gob.pe/tendencias. Web: 27/06/2013>.

6 Según cifras del año 2009-2010 del reporte de la Unesco (2012) de acceso a Internet de Primaria-Secundaria, el país estaría ubicado apenas por encima de países como Nicaragua (4-9%%), Paraguay (8-18%) y Venezuela (20-15%). Frente a ello, países de la región como Argentina (29-50%), Brasil (41-76%), Chile (55-56%) y Colombia (66-93%) se encuentran muy por encima, sin contar a los países de Asia y Europa, cuyo porcentaje de conectividad en las escuelas es muy cercano al 100%.

There is a lag in adoption by rural schools compared to schools located in urban areas. In 2004, less than 1% of rural schools were connected to the Internet; today, despite the large improvements (9%), the disparity remains.

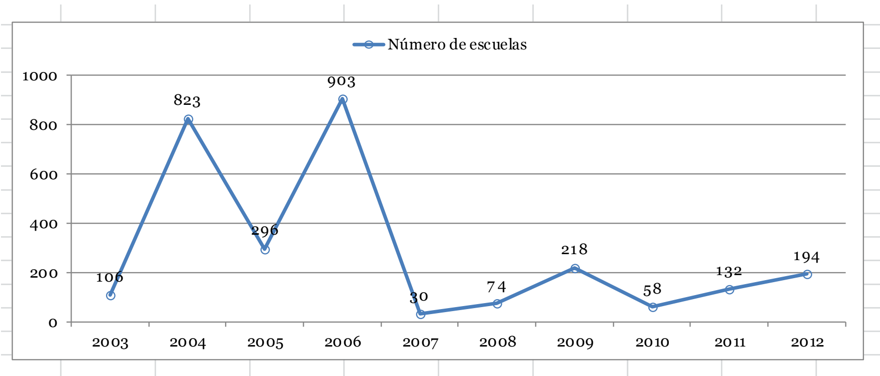
In regard to the government-promoted initiatives that seek to integrate ICTs within the educational environment, the Ministry of Education has been implementing diverse programs to provide the technological infrastructure, which includes ICT training for teachers and the development of digital content. Over the course of recent decades, the initiatives that have achieved the greatest level of notoriety, as a result of the political backing they have received as well as the public funds involved, are the Huascarán Program and the One Laptop per Child (OLPC) program.

The Huascarán Program, created in 2001, provided schools with subsidized connectivity (free) and saw its greatest deployment over the period of 2004-2006 in public schools.[7] While the program had the prioritization criteria and procedures for selecting the beneficiary educational institutions, in many cases they were not taken into account, and political and contextual considerations prevailed throughout the program's deployment (see Annex 1). Thus, only minimal technical criteria—technological infrastructure (wired or wireless data network, electrical wiring, protection systems) and service coverage of telecom operators—were followed, in line with the budget for the installation of connectivity.

7 Presidential decree 067-2001-PCM.

No wonder that after a series of inquiries into the management capacity and the instrumentalization for selecting beneficiaries for political purposes, the Huascaran Program was absorbed by the newly created Department for Educational Technology (DIGETE for its acronym in Spanish), along with other initiatives, in 2007, which, despite having continued to provide the service, it has not expanded access. As a result, progress in connectivity has virtually stagnated following that date (Figure 2).[8] This contrasts with, and perhaps even explains, the significant progress of the OLPC program, created in 2008, which gives XO laptops to public schools in poor districts (no Internet connectivity) with a minimum number of criteria (basic services like electricity).

Figure 2. Flow of schools served by DIGETE according to the Internet connectivity installation date



Source: DIGETE. Authors.

In 2007, a "Budget for Results" strategy was implemented in education, which marked the beginning of monitoring of learning achievements in regular basic education, with emphasis on early childhood and primary education (first and second grades). The first

8 For more information, see: DS N° 016–2007–ED "Article 49 of the ROF is amended and the merger of Projects Huascarán and PEAR is approved as well as the Program for Improvement in Secondary Education of the Ministry of Education.

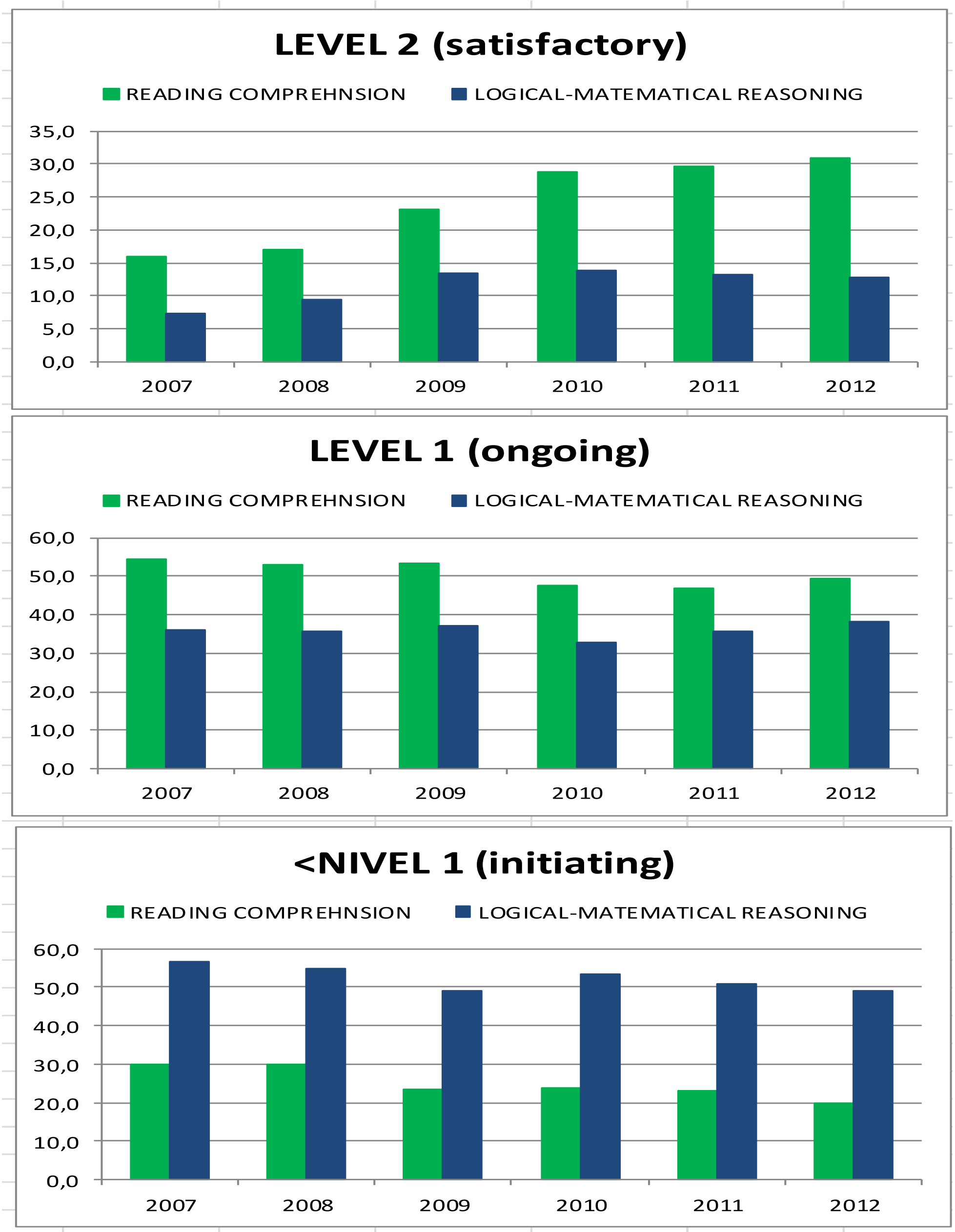
census student assessment was performed that year, with results that showed the low quality of education: only 15.9% and 7.2% of educational institutions achieved satisfactory performance in reading comprehension and logical-mathematical reasoning, respectively (see Figure 3).

Given these results, the Ministry of Education (MINEDU for its acronym in Spanish) formulated the Strategic Achievements Learning Program (PELA for its acronym in Spanish), which assesses progress in the development of education, the strengthening and specialization of teachers in public schools, distribution of educational materials, evaluations of students enrolled in public educational institutions and the regions' physical progress in covering initial education and providing their teachers with pedagogical support.[9]

To date, notable progress has been achieved in reading comprehension and logical-mathematical reasoning, although less so in the latter (Figure 3).

9 The selection of the educational institutions is subject to three criteria: (a) public educational institutions with a high poverty rate, (2) educational institutions with a low learning outcome; and (c) educational institutions with a high concentration of the student population.

Figure 3. Overall results 2007 to 2012 of the control sample (Percentage of students by performance level)



Source: Overall results 2007-2012 (control sample). Authors

4. DATABASES

The two main sources of information for the research are the CE, conducted by the MINEDU annually since 1998, in cooperation with decentralized education management agencies, and the ECE conducted since 2007. For the research, the common observations between ECE and CE for the period 2007-2011 are used, merged with the modular and Annex code so that you have a panel database.

The characteristics of each school were obtained from the CE, and the outcome variables from the ECE. Regarding the former, special care was taken in choosing the variables that can be followed during all the years of study. This is because the questions have changed over the years, the wording of the questions has changed or coding is different from one year to the next, which entails work to make the different versions of the census consistent.

The ECE is a standardized test representative of the country as a whole, given to second-grade students on two curricular areas: reading comprehension and logical-mathematical reasoning. The results of the ECE learning achievement levels are comparable for our entire analysis period. This study uses the percentage of students in second grade who achieved satisfactory performance level (level 2) in reading comprehension and logical-mathematical reasoning as outcome variables. Although we cannot follow the same students over time, we can see the performance of each new cohort of second graders to infer the impact of Internet access on educational performance so that our unit of analysis would be an indicator of academic performance for a school followed over time.

Information on the treatment variable—Internet connectivity—comes from the CE module for the school district, which contains data regarding infrastructure, utilities and installations, among others. This information is complemented by data provided by the MINEDU on subsidized connectivity provided by the State through DIGETE because some schools did not report having Internet access on the census, but were in DIGETE's database. This administrative record contains the date and type of installation (bandwidth) and the contract for each of the participating schools. DIGETE's information can be exploited to study potential heterogeneous effects according to the type of Internet access. In addition, the altitude of the district is used to capture geographic differences between schools and their relationship with the ease of providing Internet access service.

The main limitation of the previously described databases is that they do not collect information on socioeconomic variables related to the students or their homes. To the extent that the evaluation design must consider the possible sources of heterogeneity in the responses given by those accessing treatment, we propose that the following information be used in addition: the XI National Census of Population and the VI Housing Census (2007), the IX Population Census and the IV Housing Census (1993) and indicators from the 2007 Poverty Map created based on the 2007 Census, to capture the average characteristics of the population of the district where each school is located.

5. Econometric Methodology

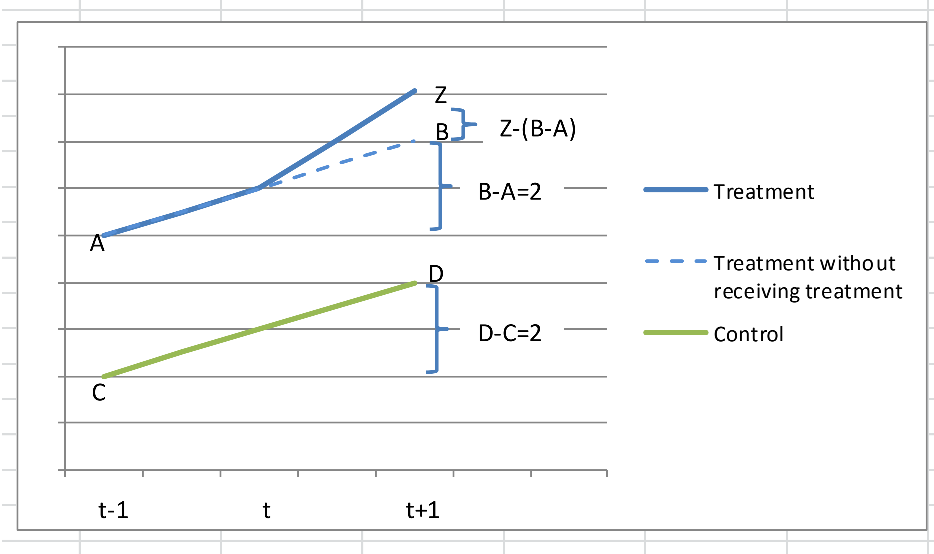
What do we want to estimate? We are aiming to calculate the effect Internet access and access to high-speed Internet have on educational achievement.[10] In order to do this, we need to know what would have happened in those schools that agreed to this service in the event that they had not done so. Clearly, this second scenario is impossible to observe. Herein lies the fundamental problem of any impact assessment (Khandker, Koolwal and Samad, 2010): find this counterfactual. Explicitly, the problem is finding the second term of the following equation:

$$E(Y_{1i}|d_i = 1) - E(Y_{0i}|d_i = 1)$$

In line with Figure 4, we want to estimate the effects on the treatment group with Internet access at the moment t. To this end, we assume that the trend of those not part of the treatment group, points C and D, would have been the same for the treatment group if they had not accessed the service (points A and B). Thus, the net effect of Internet access would be the difference between Z and A, discounting the trend of those not in the treatment group, B-A, which, clearing terms leave us the result Z-B, equivalent to the previous equation. As can be seen, we estimate B based on what happens with the observations of those who do not access the Internet.

10 *Es posible que otras escuelas tengan Internet de alta velocidad por otro medio además de la DIGETE por lo que más adelante se detalla la estrategia de identificación que evita este potencial sesgo.*

Figure 4 Difference-in-Differences Estimator



The econometric alternatives of the impact assessment that can be applied depend on the type of data that is available. As mentioned in the previous section, the available information allows us to build a school-level panel database and estimate the impact for Difference-in-Differences (DD). However, this estimator does not control for the schools' observable characteristics. An alternative is to present a classical linear regression model and control for observable variables (in the schools and district) assuming a linear relationship between these control variables and the outcome. In this paper, we propose the relationship between observable characteristics and variable Y be estimated using non-parametric quasi-experimental evaluation methods, whose main advantage is greater freedom to find better counterfactuals.

First we analyze the derivation of the Propensity Score Matching (PSM) estimator for a cross section sample and then include the characteristics of Difference-in-Differences (DD) estimator for a sample of panel data in an effort to derive the estimator PSM-DD.

Formally, following the approach of Blundell and Costa Dias (2000), we have:

(1)
$$Y^T = g^T(X) + U^T$$
$$Y^C = g^C(X) + U^C$$

Where the outcome variable Y of T and C, the treatment and control groups, respectively, depend on a function g (X) of the observable characteristics X and an error term U. The difference between the two equations allows us to estimate the *Average Treatment Effect on the Treated (ATT):*

(2)
$$\text{ATT: } \alpha_T = E(Y^T - Y^C \mid X, d = 1)$$

This approach assumes conditional independence between the control group C and the decision to participate in the program, namely:

(3)
$$Y^C \perp d|X$$

Decomposing the ATT α_T:

(4)
$$E(Y^T - Y^C|X, d = 1) = [E(Y^T|X, d = 1) - E(Y^C|X, d = 0)] - [E(Y^C|X, d = 1) - E(Y^C|X, d = 0)]$$

Following Rosenbaum and Rubin (1983), the dimensionality problem of X can be simplified by using the probability of participation in function to X as a single indicator to match observations:

$$Y^C \perp d|P(X)$$

(5)

Thus, the corresponding estimate is:

(6)
$$\widehat{\alpha} = \sum_{i\epsilon T}^{N_T} \left(Y_i - \sum_{j\epsilon C}^{N_C} W_{ij} Y_j \right) w_i$$

Where W_{ij} is a weighting factor of observation of the control j for the treatment individual i and w_i is the weighting factor that adjusts the distribution of result to the treated sample. These weighting factors depend on the matching method used. For example, in the case of the nearest neighbor(NN), the estimator is:

(7)
$$\widehat{\alpha}_{NN} = \sum_{i\epsilon T}^{N_T} \left(Y_i - Y_j \right) \left(\frac{1}{N_T} \right)$$

However, it should be assumed that (3) or (5) are strong assumptions, especially if individuals can choose whether to participate in the program based on their prediction of the expected result of doing so. Using Difference-in-Differences (DD), this unobservable variable can be isolated. Consider the following alternative structure to (1):

$$Y^{T}{}_{it} = g^{T}{}_{t}(X) + \theta_t^T + u^{T}{}_{it} + \varphi_i$$

(8)
$$Y^{CT}{}_{it} = g^{C}{}_{t}(X) + \theta_t^C + u^{C}{}_{it} + \varphi_i$$

Where the function g() changes over time and the outcome variable is controlled based on characteristics of the analyzed period θ and individual characteristics φ.onces, conditions (3) and (5) can be expressed as:

$$Y^{C}{}_{t1} - Y^{C}{}_{t0} \perp d|X$$

9)

$$Y^{C}{}_{t1} - Y^{C}{}_{t0} \perp d|P(X)$$

10)

It is assumed that the difference in the result is independent of the decision of change rather than assuming independence levels. Therefore, we substitute equation (6) with the following ATT PSM-DD estimate:

(11)	$\widehat{\alpha}_{PSMDD} = \sum_{i \epsilon T}^{N_T} \left((Y_{it1} - Y_{it0}) - \sum_{j \epsilon C}^{N_C} W_{ij}(Y_{jt1} - Y_{jt0}) \right) w_i$

A key distinction between the DD method with linear controls and PSM-DD is the interpretation of the control variables. In the first method, the control variables play the role of explanatory variables for the endogenous variable "percentage of second-grade students who achieve satisfactory level of knowledge." While in the second method, the control variables are used to explain the probability of access to the Internet and thus find similar schools and the main difference is the access or not, and then comparing the endogenous variable of interest. This should be taken into consideration when interpreting the results.

6. IDENTIFYING THE IMPACT OF INTERNET ACCESS

How does one study the effect of Internet access on the academic performance of students? The ECE makes it possible to measure year-on-year school performance of second-grade students at the level of modular + Annex code for the period 2007-2011. Then, all possible dynamics of Internet access over this period and which schools are to be studied must be determined. Table 2 illustrates these possible dynamics, taking those schools that did not have Internet access in 2007 as a starting point and the number of schools for each type of access dynamic.

Table2. Evaluated dynamics of Internet access

Groups	Access (1) and no access (0) to the internet					Number of schools Panel 2007-2011
	2007	2008	2009	2010	2011	
I	0	1	1	1	1	141
II	0	0	1	1	1	145
III	0	0	0	1	1	373
IV	0	0	0	0	1	1.293
V	0	0	0	0	0	20.057
Total						**22.009**

Sources: ECE 2007-2011, CE 2007-2011 y Digete 2012.

Note: Only those schools with no access to the Internet in 2007 are considered. The authors.

Two exclusion criteria were used to consider only schools in which Internet access could have a constant transmission channel toward educational performance and to define a counterfactual group with these transmission channels but not Internet access. First, schools that do not follow these proposed patterns—and as a result do not allow a clear identification of the impacts assessed, such as schools that accessed the service in year t but no longer had the service in year t+k—were excluded from the analysis. Second, we excluded those schools that did not have computers for teaching over the period of at least one year from the date of impact assessment t and the year t+k. Based on this, it is assumed that without computers designated for educational use there are no channels of transmission between Internet access and educational performance. To assume the contrary would require the consideration of schools that do not have these assets. Therefore, the evaluated impact would not be Internet access but rather Internet access plus access to a computer designated for educational use.

The second question is when to measure the impact? We have opted to assess the impact based on the ECE for the year following Internet service access. For example, if the school accessed the service in 2008, we can assess its impact in 2009, 2010 and 2011, differentiated with respect to the outcome variable of 2007, . and thus have a kind of approximation to the "size of the dose" of treatment, which can also be understood as teachers' appropriation and better use of the Internet access. Due to sample size, those schools that accessed Internet services in the year for which the impact is being evaluated are not excluded. That is, in the case of evaluating the effects on schools that accessed the Internet in 2008 (group I) and its impact on educational performance for 2009, group II (those schools that accessed the service in 2009) was not excluded from the analysis. It is assumed that Internet access does not produce an impact in the same year of initial access to the service, which is a valid assumption considering that treatment exposure would be minimal. The comparison is made with respect to the groups II + III + IV + V.

Thus we have two options for evaluation: dynamic effects of impact and the effect the following year. The years and the various groups used to assess the impact of Internet access in year t are summarized in Table 2.

Table 3. Assessment schematic

	I-Dynamic effects		
Group	**Performance result *t+k* in respecto to the year *t-1***		
I vs IV+V	2009	2010	2011
II vs IV+V		2010	2011
	II-Effect at 1 year of access		
Group	**Resultado *t+1* respecto a *t-1***		
I vs II+III+IV+V	2009		
II vs III+IV+V	2010		
III vs IV+V	2011		

Authors.

On the other hand, the advantage of this scheme of analysis is that it helps strengthen the results in the face of a possible bias due to the endogeneity in Internet access. Schools that first accessed Internet services probably have better initial infrastructure in the school and at the district level alike, compared to schools that did not have access to the service or accessed the service later. Similarly, the exclusion criteria can minimize this potential bias.

7. IDENTIFYING THE IMPACT OF BROADBAND INTERNET ACCESS

Before discussing the strategy for identifying the impact of broadband Internet access, the databases available for this purpose will be reviewed, and a statement of its limitations made. Finally, the identification strategy is presented in line with the chosen database.

Database used for broadband analysis

The database used for the analysis of the impact of broadband Internet access pertains to the DIGETE-Huascarán Program for the years 2003-2012.

It presents information by type of access for schools served by the program, which represent a very specific group within the total number of schools. The criteria used to determine if a school was eligible for the program were systematized based on Annex 1 and are presented in Table 4..

Table 4. Criteria for selecting the educational institutions eligible to participate in the Huascarán Program

1	Public management, rural or inner city areas.
2	Peripheral fence and electricity (adequate infrastructure).
3	Available and safe room (similar to point 2?).
4	Districts not served to date (preferably) except for the city of Lima and Callao.
5	Sort by number of students from highest to lowest.

Source: MINEDU web site

The database identifies the type of Internet access technology. This makes it possible to define those schools with Internet access based on a type of high-speed technology. Schools with access to broadband Internet are defined as those with ADSL and VPN technology. Because data on educational performance results are for the period 2007-2011, the proposed DD and DD-PSM methodology are used to evaluate only those schools that accessed the Internet service between 2008 and 2010.[11] Table5 summarizes the number of observations by type of Internet access technology for the years assessed.

Table 5. Internet access by type of technology, 2008-2010

Type of access	2008	Year 2009	2010	Total
IP ADSL	0	0	42	42
IP VPN	0	0	16	16
VSAT	74	218	0	292
Total	74	218	58	350

Source: DIGETE-Huascarán Program

This is the most reliable database for identifying beneficiaries of broadband Internet access. However, there are only 58 schools that accessed the service in 2010.

<u>Identification</u>

Because schools only accessed broadband Internet services in 2010, we can only estimate the impact on educational performance for 2011. In order to define the counterfactual group of schools, the criteria in Table were used as a base; these are summarized in Table, summarized in Table

11 It is possible to do the analysis at the cutoff level but because unobservable characteristics between schools will not be controlled, this would increase the potentialbias of the impact estimator.

6 including some criteria to standardize the characteristics of the counterfactuals against the treated.

The result is a sample of 1871 schools. Furthermore, after combining DIGETE's database with the ECE panel for 2009-2011, there are 41 treatment schools instead of the 58 that accessed the service according to DIGETE.

Table 6. Exclusion criteria for identifying the counterfactual group

Excluded schools include those that:	
1	*are private institutions (i.e., not public).*
2	*with no electrical power.*
3	*belong to a district serviced by the Huascarán Program during the period 2003-2009.*
4	*had Internet access during the period 2007- 2010.*
5	*are mixed-teaching schools.*
6	*the % of rural population in 2007 was higher than the maximum % of the rural population in the treatment group.*

Source: DIGETE- Huascarán Program, CE (2007-2011), ECE (2007-2011) Population and Housing Census (2007).

8. RESULTS

8.1 Internet access

The attempt was made to work with the same specification for all of the regressions; the only change made being the year of the variables of the educational institution based on the year Internet service was accessed. This controls by the variables in the base year prior to accessing the service (t-1) and by changes in some variables between the base year and the year of access (t-1 vs. t) and the year of assessment (t-1 vs. t+k). However, it was not always possible to use the same specification because not all specifications satisfy the balancing condition of the PSM. Therefore, we sought to omit from these regressions the lowest number of variables in order to maintain a greater consistency and robustness between different estimators calculated and between the two samples processed.

Furthermore, as an intermediate step between the method of DD and DD-PSM, the DD estimates with linear controls are placed through an ordinary least squares (OLS) regression using the same specifications as logistic regression models.

Due to the sample size, pairing was done with replacement and allowing the use of several observations in the event of the same pscore. Three matching methods were used:[12] one-to-one, radius and kernel. The first is an special case of pairing by nearest neighbor(s), in which the only school chosen is the one with a pscore closest to each school in the treatment group. Pairing using the Radius method matches within a

12 The algorithms used are outlined in Annex 8.

radius of tolerance defined by a caliper or radius of tolerance. Unlike one-to-one matching, the radius method compares against all the observations in the nearest neighborhood. Finally, the kernel estimator constructs a counterfactual school weighing the pscores estimated in the logistic regression model. An advantage of the Kernel estimator is that there is less variance due to the greater volume of information used, but it can lead to bad matches, which affects the results even though they are weighted by the estimated pscore. The opposite case is the one-to-one estimator that increases the matching accuracy by using only the nearest neighbor but increases the variance by using fewer observations. Radius matching is an intermediate case in which the caliper avoids matching closest observations with a distant pscore, while also taking advantage of all available information within a neighborhood. The observations within the neighborhood are weighted according to their pscore (Caliendo, M., & S. Kopeinig. (2005).

Descriptive statistics of the main variables used in the match, both at district level and at the level of the educational institution are presented in the Annex 2-5. One of the factors that stands out the most is that the average altitude of the district capital of the district where the EI is located is lower in the case of institutions with Internet access than those without access. This suggests a possible tendency to provide service in the most accessible areas or geographically better connected. Similarly, the no-treatment group IV + V comprises a high percentage of public schools, while the treatment groups I, II and III are mostly private mixed-age schools. Despite this, the ranges of the variables for the most part coincide, which favors the application of the matching method.

Next, the parallel trend assumption is examined. Because there is no test for this assumption in the case of non-experimental assessments, Figure 5 enables us to analyze if there is any reason to suspect that it is not being followed.[13] To do this, the outcome variable "% of students at Level 2 of educational performance" is plotted to assess whether there is a change in trend among any of the test groups. Because at least 2 points before Internet access are needed, the result variable from group II and III are compared with the control group IV + V. The charts suggest that both curves move parallel before treatment. Therefore, the parallel trend assumption is assumed. Also, a fact that is evident from Figure 5 and

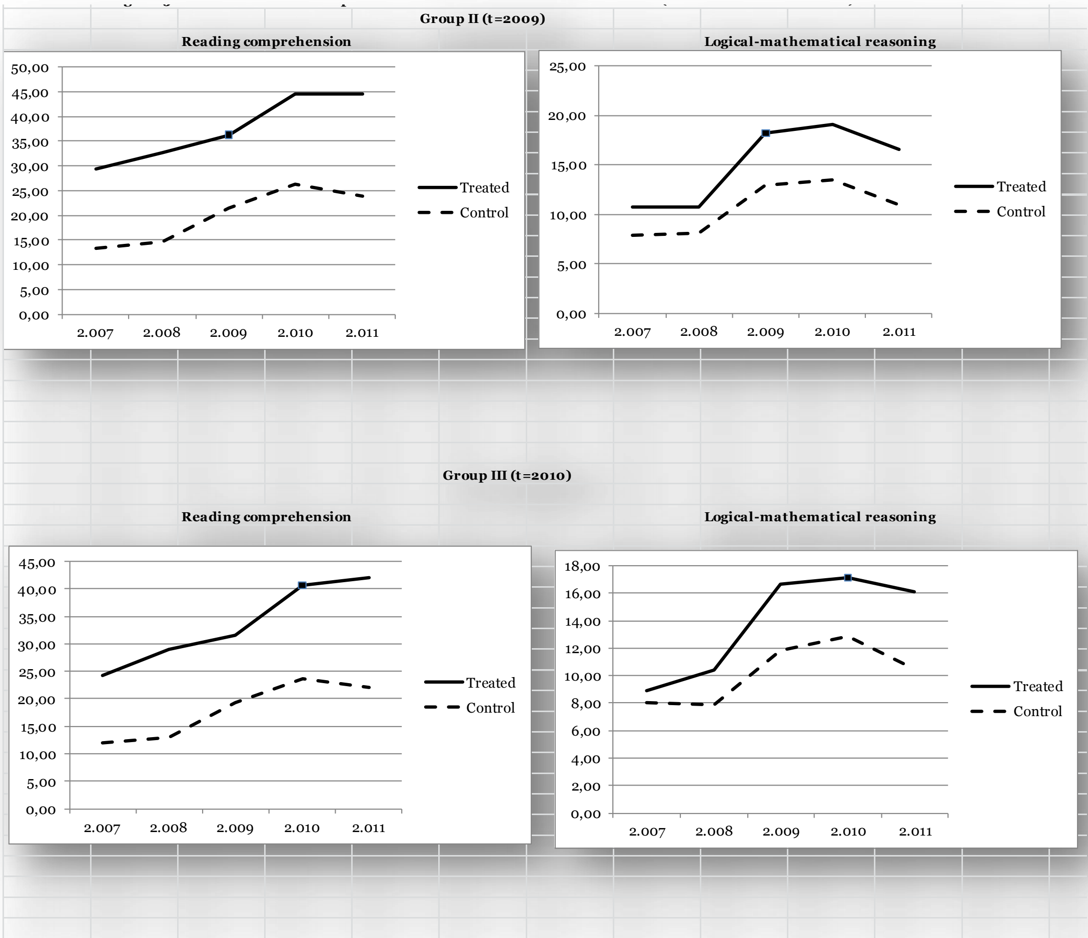
Figure 3 (Section 3) is the rapid growth in the percentage of students with Level 2 academic performance among the treatment and control groups alike; particularly between 2008 and 2010 in the case of reading comprehension results and between 2008 and 2009 for logical-mathematical reasoning. One possible cause is the cumulative effects of several of MINEDU's efforts to improve the educational performance of

13 In Randomized Controlled Trial (RCT) assessments, this assumption is tested by assigning placebo-type treatments, which would give us indirect evidence of the parallel trends assumption..

students, such as the Strategic Program Learning Outcomes (PELA for its acronym in Spanish), whose intervention actions are based on traditional tools such as educational materials, teacher training and support, etc.[14]

Figure 5. Parallel trend assumption - Difference-in-Differences Method (% of students at Level 2)

14 "First implemented in 2008 at the primary level, starting in 2009, PELA was extended to preschool and primary levels in the regions of Ayacucho, Apurímac, Huancavelica, Huánuco, Lima Provincias (Lima Region), the city of Lima and Callao and in the VRAE areas of Junín and Cusco" (Source: PELA web site, http://ebr.minedu.gob.pe/dep/peladep.html)



As mentioned in the presentation of the econometric strategy, the OLS model can explain the endogenous variable of interest through the impact variable and other explanatory variables. OLS results are presented in Annex 7 and 8. Using this estimation method makes it possible to find differential effects of the control variables according to the treatment and control group used. The variables that explain a negative effect on educational performance with the most statistically significance are socioeconomic ones, such as the poverty gap in the district, the percentage of people with access to public services (water, drainage and lighting) and the growth rate of the intercensal population. Income inequality measured by the Gini coefficient has ambiguous effects (negative, null and positive) according to the comparison group. This suggests that the econometric Difference-in-Differences strategy with linear controls may not be adequate for identifying the impacts of Internet access on educational achievement.

The results of logistic regressions to estimate the probability propensity to belong to the treatment group of schools evaluated are presented in Annex 9. This econometric method changes the form of interpretation of the control variables. It is found that those with access to public services such as water and sewer, as well as a greater number of computers, are more likely to access the Internet. Similarly, public schools have a negative probability of accessing the service. Likewise, the poverty gap and the low connectivity of telecommunications services in the district in which they are located have a negative effect on the probability of having Internet access.

Table 7 presents the results of ATT estimates of dynamic effects after one year of Internet access. The three estimation methods: DD, DD with linear controls and DD-PSM are compared. The estimated coefficients are interpreted as the largest percentage of students with Level 2 educational performance subtracting the tendency in which this percentage would have increased if they had not accessed the Internet service.

Dynamic effects

According to the results of the 2007-2011 panel, the cumulative effect is predominantly positive, although the statistical significance depends on whether or not controlling for observable variables, the year assessed and the method of estimation. Without controlling for observable variables, the impacts are positive and significant in reading comprehension performance in 2010 and 2011 only for the first schools that accessed Internet service in 2008 (Group I) and in 2011 in the case of those that accessed the service in 2009 (Group II).

Observing only estimators without observable control variables, it is suggested that the cumulative effect is greater for those schools that accessed the Internet in 2008. However, controlling for observable variables, the effects are diluted without controls and only in 2011 are any statistically significant effects found. For the first treatment group, the linear OLS specification for 2011 estimated a positive and significant impact to a level of confidence greater than 95%, while in other cases the confidence level is even lower than the benchmark value of 85%. With respect to the Group II treatment, the impacts are mostly null except the DDPSM Kernel estimator for 2011 which has a positive impact with a significance level greater than 15%, i.e., of a low level of statistical confidence. A similar pattern is observed in the performance of logical-mathematical reasoning which is only significant at the 10% level if not controlled for observable variables.

If we only consider the coefficients estimated with control variables, a positive impact range for the assessment years 2011 is found. For Group I, the impact on the percentage of students who achieved a satisfactory level of knowledge in text comprehension is between 0% and 5.8% and logical-mathematical reasoning between 0% and 3.7%. Group II shows a positive impact on reading comprehension in the range of 0% and 4.9%. Then, according to the results of estimates of dynamic effects, it is suggested that there is a "year effect" in 2011 in the percentage of students who reached the satisfactory level of knowledge in favor of schools that accessed the Internet service.

Effects at one year

Unlike the estimator of cumulative effects, the effects estimator at one year allows a comparison with a larger group of no-treatment schools, including those that will have Internet the following year. Thus, we have control schools that are more similar to the treated schools, which would reduce the standard deviation of the estimated coefficients.

The impact of Internet access is positive and significant in logical-mathematical reasoning for schools that accessed the service in 2008 (Group I), with and without control variables, although the estimation method used influences results. For 2011, these effects are positive and significant only for the Radius and Kernel estimators DDPSM but weaker than in 2008. Regarding performance in reading comprehension, the impact is positive and significant for schools that accessed the Internet in 2010. These results remain robust when including control variables, regardless of the estimation method. Thus, the percentage of students with a satisfactory level of performance in reading comprehension rose from 5.2% to 6.9% in 2011. For logical-mathematical reasoning sense, there is an effect between 0% to 2.9%.

These results suggest that there is a greater impact on reading comprehension than logical-mathematical reasoning, and that these are concentrated in 2011, confirming the hypothesis of the “year effect” suggested based on the estimators of dynamic effects.

Table 7 Results: Effects of Internet access in Peru, 2007-2011

Dynamic effects

	Reading comprehension						Logical-mathematical reasoning				
	DD without controls	DD with linear controls	DD with PSM controls				DD without controls	DD with linear controls	DD with PSM controls		
			One to one	Radius	Kernel				One to one	Radius	Kernel
Group I vs IV+V: Access a Internet in t=2008 assessed in t-1 vs t+1, t+2 and t+3											
$b_{2009-07}$	1,873	1,654	0,816	1,274	1,296	$b_{2009-07}$	8,305***	2,635	4,682	0,520	2,094
	(2,012)	(2,725)	(4,283)	(3,525)	(3,357)		(2,069)	(2,749)	(3,898)	(3,711)	(3,059)
$N_{2009-07}$	1.203	826	826	826	826	$N_{2009-07}$	1.211	932	832	832	832
$b_{2010-07}$	6,467***	2,914	3,083	3,897	3,996	$b_{2010-07}$	9,429***	2,385	-0,217	0,003	2,888
	(2,012)	(2,619)	(4,307)	(3,706)	(3,549)		(2,106)	(2,759)	(3,621)	(3,369)	(2,780)
$N_{2010-07}$	1.169	804	804	804	804	$N_{2010-07}$	1.183	917	817	817	817
$b_{2011-07}$	9,815***	5,888**	0,781	5,187	4,657	$b_{2011-07}$	9,326***	3,765+	-0,900	0,512	2,458
	(1,948)	(2,545)	(4,141)	(3,691)	(3,528)		(2,013)	(2,577)	(3,505)	(3,257)	(3,132)
$N_{2011-07}$	1.208	840	840	840	840	$N_{2011-07}$	1.219	847	847	847	847
Group II vs IV+V: Access a Internet in t=2009 assessed in t-1 vs t+1 and t+2											
$b_{2010-08}$	2,797	-0,413	-2,028	-0,324	1,730	$b_{2010-08}$	2,729	-0,546	0,497	-0,768	1,149
	(2,071)	(2,397)	(3,854)	(3,055)	(2,612)		(2,000)	(2,432)	(3,680)	(2,799)	(2,468)
$N_{2010-08}$	1,619	1,063	1,063	1,063	1,063	$N_{2010-08}$	1,620	1064	1,064	1,064	1,064
$b_{2011-08}$	4,909**	1,953	5,168	3,770	4,872+	$b_{2011-08}$	3,824**	0,692	2,783	2,151	2,250
	(1,932)	(2,320)	(4,313)	(2,789)	(3,109)		(1,854)	(2,292)	(3,462)	(2,478)	(2,647)
$N_{2011-08}$	1.630	1.079	1.063	1.079	1.079	$N_{2011-08}$	1.630	1079	1.079	1.079	1.079

Effects at 1 year

	Reading comprehension						Logical-mathematical reasoning				
	DD without controls	DD with linear controls	DD with PSM controls				DD without controls	DD with linear controls	DD with PSM controls		
			One to one	Radius	Kernel				One to one	Radius	Kernel
Group I vs II+III+IV+V: Access a Internet in t=2008 assessed in t-1 vs t+1											
$b_{2009-07}$	2,833+	2,822	3,664	2,795	4,448+	$b_{2009-07}$	8,270***	3,891+	4,082	2,877	5,610**
	(1,941)	(2,488)	(3,754)	(3,169)	(2,864)		(1,966)	(2,478)	(3,499)	(2,825)	(2,689)
$N_{2009-07}$	1.645	1.098	1.098	1.098	1.098	$N_{2009-07}$	1.655	1.104	1.104	1.104	1.104
Group II vs III+IV+V: Access a Internet in t=2009 assessed in t-1 vs t+1											
$b_{2010-08}$	3,040	0,636	1,118	2,360	2,622	$b_{2010-08}$	2,799	-0,096	0,408	-0,044	1,638
	(2,113)	(2,380)	(3,295)	(2,587)	(2,164)		(2,028)	(2,306)	(3,091)	(2,250)	(2,009)
$N_{2010-08}$	1.909	1.219	1.219	1.219	1.219	$N_{2010-08}$	1.909	1.220	1.220	1.220	1.220
Group III vs IV+V: Access a Internet in t=2010 assessed in t-1 vs t+1											
$b_{2011-09}$	7,346***	5,271***	5,645**	6,879***	6,237***	$b_{2011-09}$	0,137	2,092	3,672	2,890+	2,697*
	(1,366)	(1,755)	(2,617)	(1,888)	(1,822)		(1,190)	(1,523)	(2,691)	(1,794)	(1,618)
$N_{2011-09}$	2.826	1.588	1.588	1.588	1.588	$N_{2011-09}$	2.827	1.588	1.588	1.588	1.588

Level of significance: ***: 0,01%, **:0,05%, *:0,1%, +:0,15.

Standard errors in parenthesis

The authors

8.2 Broadband Internet access

Like the previous results, estimates of logistic regression models can be viewed in Annex 10. The same care was taken to maintain the same specification for both models estimated. However, some variables had to be omitted due to collinearity.

The tables presented in Annex 4 and 6 present descriptive statistics at the district level and EI, respectively. Unlike the groups to identify the impact of Internet access, the averages are more similar. Even the altitude variable is similar on average although the standard deviation is more than 1000 m.a.s.l. Common ranges of variables between control and treatment groups improved the implementation of the PSM.

Two assessment models are presented to best exploit the few observations available for the evaluation of broadband Internet access in educational performance. Model 1 includes all educational institutions that accessed to high speed Internet in 2010. However, several of these institutions already had Internet access before accessing a higher speed so the estimated effect would be biased. Therefore, the second model excluded those IEs that in 2009 and/or 2008 had Internet access. The results of both models are presented in Table 9.

The impact is positive only in Reading Comprehension in Model 2 for the DD estimate without control variables. Controlling for observable characteristics, all estimators are statistically null at 10% significance, although the estimator using the Radius method has a confidence level of 85%. In spite of the statistically null impact, it is notable that the ATT estimator tends to be negative in the performance of logical-mathematical reasoning for both models.

Table 8. Results: Broadband Internet access in Peru

Model 1
Broadband access in 2010
Effects at one year

	Reading comprehension				
	DD without controls	**DD with linear controls**	**DD with PSM controls**		
			One to one	**Radius**	**Kernel**
$b_{2011-09}$	3,740	0.178	1,913	0,656	1,665
	(3,029)	(3.467)	(4,143)	(3,190)	(3,137)
$N_{2011-09}$	1.788	1.276	1.270	1.270	1.270
	Logical-mathematical reasoning				
	DD without controls	**DD with linear controls**	**DD with PSM controls**		
			One to one	**Radius**	**Kernel**
$b_{2011-09}$	-1,896	-2.135	-0,620	-1,874	-1,481
	(2,636)	(3.052)	(3,753)	(2,126)	(1,910)
$N_{2011-09}$	1.789	1.276	1.270	1.270	1.270

Modelo 2
Broasdband access in 2010 given that there was no Internet access in 2009
Effect at one year

	Reading comprehension				
	DD without controls	**DD with linear controls**	**DD with PSM controls**		
			One to one	**Radius**	**Kernel**
$b_{2011-09}$	6,902*	6.866	7,147	6,650+	1,665
	(4,028)	(4.842)	(6,020)	(4,106)	(3,137)
$N_{2011-09}$	1.770	1.261	1.255	1.255	1.270
	Logical-mathematical reasoning				
	DD without controls	**DD with linear controls**	**DD with PSM controls**		
			One to one	**Radius**	**Kernel**
$b_{2011-09}$	-1,791	-2.756	-1,473	-3,309	-2,306
	(3,511)	(4.274)	(5,744)	(2,389)	(2,098)
$N_{2011-09}$	1.771	1.261	1.255	1.255	1.255

Level of significance: ***: 0,01%, **:0,05%, *:0,1%, +:0,15.

Standard errors in parenthesis

The authors

Conclusion

This research set out to identify the causal effect of Internet access and broadband Internet access on educational performance. For this, a strategy for identifying multiple effects was designed, taking into consideration that those schools that first accessed the service may have unobservable characteristics linked to other factors that would bias the results. The use of three matching methods was proposed in order to strengthen the results.

In regard to the identification of the impact of broadband Internet access, a description of the available databases that could be used for future research was presented. We chose to use the database that allowed a clearer identification of the causal effect despite having a small number of observations in the treatment group. One advantage was the large number of possible counterfactuals.

The impact of Internet access on educational performance is unclear. Effects are differentiated between reading comprehension and logical-mathematical reasoning and year-to-year. The strongest effects seem to be present in the area of reading comprehension rather than logical-mathematical reasoning and highest in 2011.

Table 9 presents a summary of these results. Regarding cumulative effects, there is an increase in the percentage of students at Level 2 of educational performance of up to 5.8% in reading comprehension and 3.7% in logical-mathematical reasoning for the period 2007-11. For previous years, there are no statistically different effects from zero. There are positive and significant effects at one year of Internet access in logical-mathematical reasoning, between 0 and 5.6% in 2009 and 0 to 2.9% in 2011. In regard to reading comprehension, the impact is between 0 and 4.5% in 2009 and 5.2% to 6.9% in 2011.

Also, the impact of broadband Internet access on educational performance is statistically null, except the reference value of 6.6% in the estimator DDPSM using the Radius method in Model 2, with a confidence level of 85%. These results may be due to deficiency in teacher training or a reduction in the role of teachers due to expectations about the role of technology in education (Villanueva Mansilla and Olivera, 2012). Similarly, the shortage of assisted learning programs may be causing these null effects (Lee, L. & O'Rourke, M., 2006).

A pending issue is to study the effects on levels of educational performance below level 1, because it is possible that the results at level 2 are null for the most part, but there may be a positive effect in a higher percentage of lowering performing students that make it to level 1. In addition, taking a harder look at this problem by assessing general cognitive skills that Internet access may result in positive impacts is recommended (Cristiá, J., S. Cueto, P. Ibarrarán, A. James and E. Severin, 2011 and Johnson, 2006).

Table 9. Summary of results. Internet access in Peru. Range of impacts

	Dynamic effects	
Impact	**Reading comprehension**	**Logical-mathematical reasoning**
$b_{2009\text{-}07}$	0	0
$b_{2010\text{-}07}$	0	0
$b_{2011\text{-}07}$	0 - 5,8%**(MCO)	0 - 3,7 %+(MCO)
$b_{2010\text{-}08}$	0	0
$b_{2011\text{-}08}$	0-4,9%+(Kernel)	0
	Effects at one year	
Impact	**Reading comprehension**	**Logical-mathematical reasoning**
$b_{2009\text{-}07}$	0-4,5%+(Kernel)	0-3,8%+(MCO) y 5,6%**(Kernel)
$b_{2010\text{-}08}$	0	0
$b_{2011\text{-}09}$	5,2%***(MCO)-6,9%***(Radius)	0-2,7 %*(Kernel) y 2,9%+(Radius)

Level of significance: ***: 0,01%, **:0,05%, *:0,1%, +:0,15.

Estimation method in parenthesis

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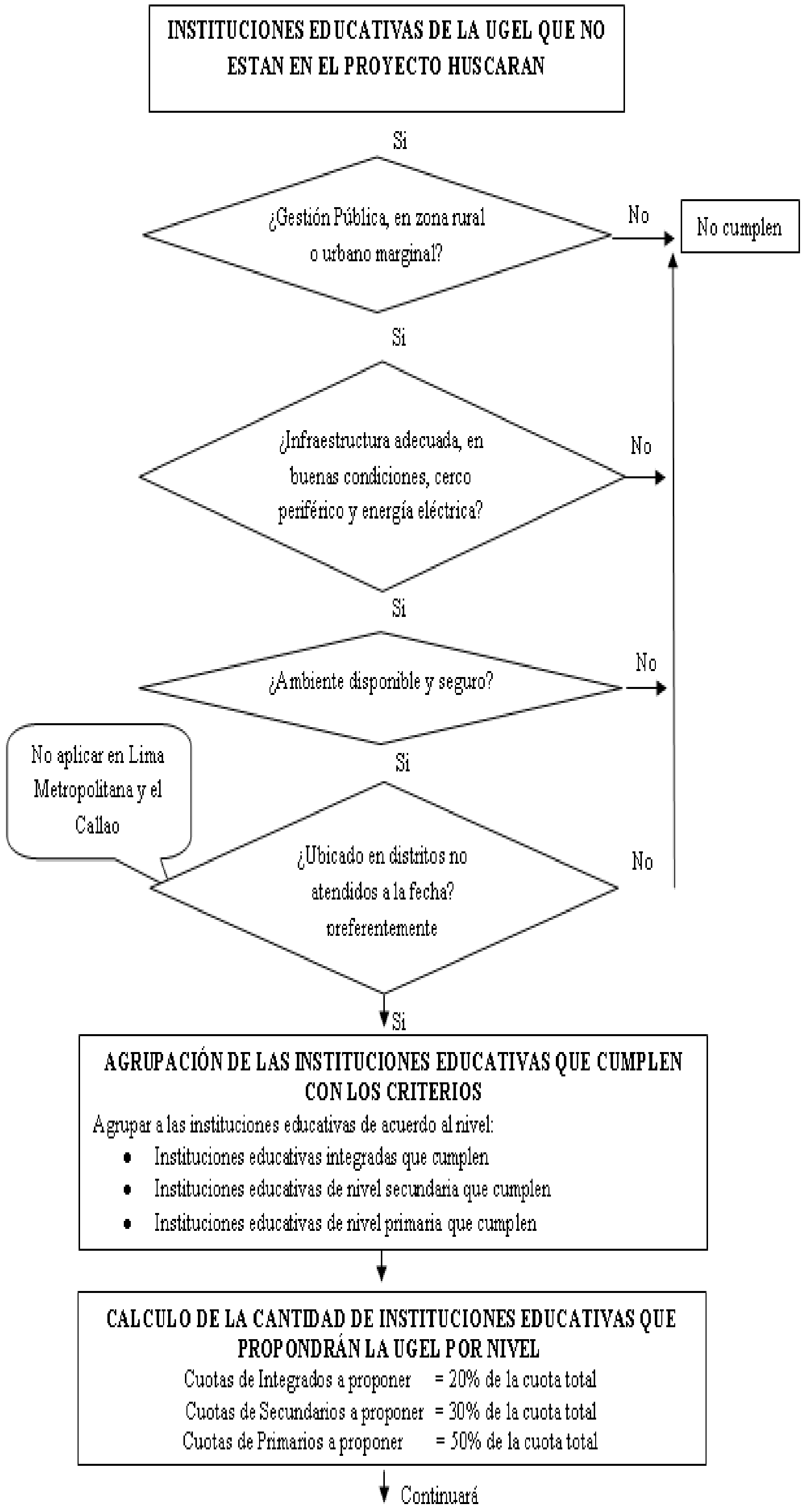
ANNEX 1 :

Prioritization criteria for the selection of educational institutions for Project Huascaran as they appear on the MINEDU web site



Sigue

SELECCIÓN DE INSTITUCIONES EDUCATIVAS INTEGRADAS QUE SERÁN PROPUESTAS

Las instituciones educativas Integradas que cumplen deberán ser ordenadas de mayor a menor población estudiantil.

Luego se seleccionará desde el primero de la lista hasta cubrir la cuota de instituciones educativas integradas a proponer

La relación obtenida hasta aquí sería serían la propuesta de instituciones educativas integradas de la UGEL.

SELECCIÓN DE INSTITUCIONES EDUCATIVAS DE NIVEL SECUNDARIA QUE SERÁN PROPUESTAS

Las instituciones educativas de nivel secundaria que cumplen deberán ser ordenadas de mayor a menor población estudiantil.

Luego se seleccionará desde el primero de la lista hasta cubrir la cuota de instituciones educativas de nivel secundaria a proponer

La relación obtenida hasta aquí sería serían la propuesta de instituciones educativas de nivel secundaria de la UGEL.

SELECCIÓN DE INSTITUCIONES EDUCATIVAS DE NIVEL PRIMARIA QUE SERÁN PROPUESTAS

Las instituciones educativas de nivel primaria que cumplen deberán ser ordenadas de mayor a menor población estudiantil.

Luego se seleccionará desde el primero de la lista hasta cubrir la cuota de instituciones educativas de nivel primaria a proponer

La relación obtenida hasta aquí sería serían la propuesta de instituciones educativas de nivel primaria de la UGEL.

ELABORACIÓN DE LA LISTA PRIORIZADA DE INSTITUCIONES EDUCATIVAS

La UGEL elabora su relación final en orden de prioridad, de mayor a menor población estudiantil, pero alternando estrictamente los criterios obtenidos, de tal manera que no se dará el caso de dos o más instituciones educativas consecutivas del mismo distrito, a no ser que ya no haya más posibilidad de alternancia.

ENVIO DE LA INFORMACIÓN DESDE LAS UGEL's

La relación final priorizada es enviada a la Dirección Regional de Educación correspondiente acompañada de las respectivas fichas de levantamiento de información de cada institución educativa (ver anexo N°2), del acta de acuerdo con la participación de los gobiernos locales y de los croquis y ubicaciones de las aulas de innovaciones pedagógicas. Adicionalmente, los datos de las instituciones educativas propuestas deberán ser registradas en la dirección web: http://selección.huascaran.edu.pe

Source: MINEDU web site. Retrieved from <http://www.minedu.gob.pe/normatividad/directivas/Dir083VMGP2003.php>. Web 24/06/2013.

ANNEX 2 :

Anexo 2 Estadísticas descriptivas de las principales variables distritales utilizadas en el PSM-Acceso a internet Panel 2007-2011								
	Grupo I+II+III				Grupo IV+V			
Variables distritales por escuela	**Media**	**DE**	**Mínimo**	**Máximo**	**Media**	**DE**	**Mínimo**	**Máximo**
Brecha de pobreza total	5,78	4,94	0,20	40,40	22,17	12,21	0,20	71,00
Coeficiente de Gini	0,30	0,03	0,21	0,41	0,29	0,04	0,19	0,43
Gasto per cápita precios de Lima Metropolitana	529,82	133,86	195,80	989,50	311,48	114,79	83,40	989,50
Proporción de la población sin agua ni desagüe de red	0,02	0,02	0,00	0,36	0,07	0,05	0,00	0,38
Proporción de la población sin alumbrado eléctrico	0,03	0,03	0,00	0,21	0,12	0,07	0,00	0,39
Proporción de la población sin servicio de información ni comunicación	0,07	0,04	0,01	0,26	0,19	0,07	0,01	0,46
Proporción de la población analfabeta	0,02	0,02	0,00	0,20	0,09	0,06	0,00	0,31
Edad promedio del distrito	29,76	2,83	22,51	40,49	26,80	3,06	18,04	42,44
Proporción de personas que viven en el área rural	0,06	0,16	0,00	0,96	0,58	0,32	0,00	0,99
Población	228.611	215.891	1.092	898.443	43.896	103.243	187	898.443
Tasa de crecimiento intercensal de la población	0,34	0,41	-0,39	2,47	0,20	0,43	-0,86	6,57
Tasa de crecimiento intercensal de la población rural	-0,29	0,45	-1,00	1,85	-0,11	0,72	-1,00	67,13
Observaciones	805				23.604			

Fuente: Censo de Población y Vivienda 2007 y 1993 y Mapa de Pobreza 2007.

Elaboración propia

ANNEX 3:

Estadísticas descriptivas de las principales variables de la Institución Educativa utilizadas en el PSM-Acceso a internet Panel 2007-2011																
Variables	**Grupo I t=2008**				**Grupo II t=2009**				**Grupo III t=2010**				**Grupo IV+V t=2008**			
	Media	**DE**	**Mín**	**Máx**	**Media**	**DE**	**Mín**	**Máx**	**Media**	**DE**	**Mín**	**Máx**	**Media**	**DE**	**Mín**	**Máx**
Altitud	586,35	1.003,54	10,00	4.449,00	594,90	1.073,79	9,00	3.878,00	858,70	1.183,17	7,00	5.066,00	1.969,71	1.465,09	0,00	5.448,00
Promedio de alumnos de 2 grado por aula t-1	20,76	12,23	1,00	106,00	18,17	12,07	1,00	114,00	17,73	9,34	2,00	47,00	12,91	9,78	1,00	228,00
Proporción de locales que contaban con agua Potable en el año t-1	0,82	0,39	0,00	1,00	0,95	0,23	0,00	1,00	0,94	0,24	0,00	1,00	0,41	0,49	0,00	1,00
Proporción de locales que contaban con Desagüe en el año t-1	0,90	0,30	0,00	1,00	0,95	0,21	0,00	1,00	0,99	0,12	0,00	1,00	0,47	0,50	0,00	1,00
Total de aulas en el año t-1	12,81	8,86	1,00	92,00	10,65	5,73	2,00	38,00	11,89	5,91	0,00	48,00	4,60	4,19	1,00	62,00
Total de computadoras para la enseñanza en el año t-1	7,22	9,15	0,00	53,00	6,26	7,30	0,00	35,00	5,27	7,02	0,00	45,00	0,83	3,03	0,00	154,00
Cambio en el número de computadoras entre el año t-1 y t	4,86	14,68	-34,00	92,00	3,31	9,98	-30,00	80,00	4,80	10,54	-21,00	116,00	0,00	3,10	-154,00	113,00
Proporción de computadoras para la enseñanza en t-1	0,75	0,32	0,00	1,00	0,64	0,37	0,00	1,00	0,59	0,40	0,00	1,00	0,59	0,43	0,00	1,00
Proporción de aulas en buenas condiciones en t-1	0,87	0,27	0,00	1,00	0,91	0,24	0,00	1,00	0,84	0,30	0,00	1,00	0,43	0,44	0,00	1,00
Número de ambientes Escolares en t-1	1,84	1,20	0,00	4,00	1,78	1,08	0,00	4,00	1,33	1,01	0,00	3,00	0,62	0,85	0,00	4,00
Proporción de escuelas polidocentes en t-1	0,89	0,32	0,00	1,00	0,89	0,32	0,00	1,00	0,87	0,34	0,00	1,00	0,28	0,45	0,00	1,00
Proporción de escuelas públicas en t-1	0,21	0,41	0,00	1,00	0,20	0,40	0,00	1,00	0,26	0,44	0,00	1,00	0,90	0,30	0,00	1,00
Observaciones	188				192				425				23.604			

Fuente: CE (2007-2011) y ECE (2007-2011).

Elaboración propia

ANNEX 4:

Estadísticas descriptivas de las principales variables distritales utilizadas en el PSM-Acceso a Internet de banda ancha

Variables	Grupo de no tratados				Acceso a banda ancha en el 2010				tenía internet en el 2009			
	Media	DE	Mín	Máx	Media	DE	Mín	Máx	Media	DE	Mín	Máx
Brecha de pobreza total	14,30	10,08	0,20	49,50	9,50	7,05	1,00	34,20	9,86	7,39	1,00	34,20
Coeficiente de Gini	0,31	0,04	0,20	0,43	0,31	0,04	0,21	0,36	0,30	0,04	0,21	0,36
Gasto per cápita precios de Lima Metropolitana	396,78	124,39	158,40	989,50	454,73	107,56	206,00	686,80	447,63	117,78	206,00	686,80
Proporción de la población sin agua ni desagüe de red	0,04	0,05	0,00	0,36	0,03	0,04	0,00	0,19	0,03	0,05	0,00	0,19
Proporción de la población sin alumbrado eléctrico	0,07	0,05	0,00	0,30	0,04	0,04	0,00	0,14	0,04	0,04	0,00	0,14
Proporción de la población sin servicio de información ni comunicación	0,14	0,08	0,01	0,41	0,10	0,05	0,02	0,26	0,10	0,06	0,02	0,26
Proporción de la población analfabeta	0,06	0,04	0,00	0,31	0,04	0,03	0,00	0,17	0,04	0,04	0,00	0,17
Edad promedio del distrito	28,25	2,66	20,89	40,49	28,49	2,37	24,32	35,00	28,48	2,75	24,32	35,00
Proporción de personas que viven en el área rural	0,23	0,22	0,00	0,65	0,16	0,22	0,00	0,65	0,19	0,25	0,00	0,65
Población	74.591	126.528	452	898.443	114.417	160.429	2.029	898.443	100.787	176.692	2.029	898.443
Tasa de crecimiento intercensal de la población	0,25	0,41	-0,86	2,56	0,23	0,36	-0,27	1,41	0,19	0,29	-0,21	1,27
Tasa de crecimiento intercensal de la población rural	-0,18	1,13	-1,00	23,48	-0,28	0,49	-1,00	1,85	-0,17	0,57	-1,00	1,85
Observaciones	2.189				45				26			

Fuente: Censo de Población y Vivienda 2007 y 1993 y Mapa de Pobreza 2007.

Elaboración propia.

ANNEX 5:

Estadísticas descriptivas de las principales variables de la Institución Educativa utilizadas en el PSM-Acceso a Internet de banda ancha (t=2010)

Variables	Grupo control				Acceso a banda ancha en 2010				Acceso a banda ancha en el 2010 dado que no tenía internet en el 2009			
	Media	DE	Mín	Máx	Media	DE	Mín	Máx	Media	DE	Mín	Máx
Altitud	1.602,84	1.530,62	5,00	4.832,00	1.454,76	1.519,08	3,00	4.375,00	1.297,31	1.508,18	3,00	4.375,00
Promedio de alumnos de 2 grado por aula t-1	23,09	8,44	2,00	82,00	26,81	9,25	12,00	56,00	26,27	7,89	12,00	45,67
Contaban con agua Potable en el año t-1	0,85	0,36	0,00	1,00	0,90	0,30	0,00	1,00	0,87	0,34	0,00	1,00
Contaban con Desagüe en el año t-1	0,94	0,23	0,00	1,00	0,95	0,22	0,00	1,00	0,96	0,21	0,00	1,00
Total de aulas en el año t-1	12,01	5,76	2,00	47,00	20,55	8,15	0,00	40,00	19,96	9,56	0,00	40,00
Total de computadoras para la enseñanza en el año t-1	3,64	6,33	0,00	86,00	13,90	16,08	0,00	91,00	12,39	12,19	0,00	46,00
Cambio en el número de computadoras entre el año t-1 y t	2,78	7,28	-58,00	89,00	5,44	13,48	-21,00	42,00	5,18	10,87	-19,00	28,00
Proporción de computadoras para la enseñanza en t-1	0,45	0,41	0,00	1,00	0,67	0,30	0,00	1,00	0,67	0,25	0,00	1,00
Proporción de aulas en buenas condiciones en t-1	0,48	0,38	0,00	1,00	0,61	0,38	0,00	1,00	0,61	0,38	0,00	1,00
Número de ambientes Escolares en t-1	0,93	0,93	0,00	3,00	1,67	1,00	0,00	3,00	1,52	1,04	0,00	3,00
Observaciones	2.189				45				26			

Fuente: CE 2009-2011 y ECE 2009-2011.

Elaboración propia.

ANNEX 6:

Algorithm and characteristics of the estimation methods

General characteristics

Algorithm:

Estimate based on the common support (common)

Default matching

Matching with other controls with identical propensity score (ties)

Estimated standard deviation by bootstrap of 100 iterations with seed 151188.

Estimation Method	***Specific characteristics***
One to one	Nearest neighbor matching
Radius	Caliper of 0.01
Kernel	Epanechnikov kernel

Source: Leuven, E. & Sianesi, B. (2003).

ANNEX 7:

Results of linear regression models-Access to Internet

GRUPO	Comprensión de textos							
	Efectos dinámicos					Efectos a 1 año		
	I vs IV+V	I vs IV+V	I vs IV+V	II vs IV+V	II vs IV+V	I vs II+III+IV+V	II vs III+IV+V	III vs IV+V
Año de acceso t=	**2008**	**2008**	**2008**	**2009**	**2009**	**2008**	**2009**	**2010**
Variables								
Acceso a la Internet	1,654 (2,725)	2,914 (2,619)	5,888** (2,545)	-0,413 (2,397)	1,953 (2,320)	2,822 (2,488)	0,636 (2,380)	5,271*** (1,755)
Promedio de alumnos de 2 grado por aula	0,033 (0,091)	0,164* (0,089)	0,108 (0,083)	0,012 (0,075)	0,103 (0,072)	0,047 (0,080)	0,013 (0,069)	0,166** (0,072)
Acceso a agua potable	-3,596* (2,141)	-1,213 (2,086)	-0,641 (1,927)	3,186* (1,775)	1,983 (1,656)	-2,025 (1,816)	2,149 (1,715)	-1,361 (1,566)
Acceso a desague	-0,542 (2,258)	2,459 (2,244)	1,733 (2,065)	1,020 (1,721)	0,785 (1,620)	-0,779 (1,882)	0,765 (1,672)	8,037*** (2,502)
Total de aulas	0,001 (0,133)	-0,228* (0,130)	0,144 (0,125)	-0,191* (0,107)	0,049 (0,104)	0,037 (0,117)	-0,178* (0,104)	0,015 (0,093)
Pared de ladrillo o bloque de cemento	-3,611* (2,089)	-1,023 (2,067)	-1,276 (1,950)	2,152 (1,567)	0,232 (1,529)	-1,320 (1,843)	2,781* (1,522)	0,121 (1,373)
Total de computadoras por aula	0,030 (0,139)	0,190 (0,135)	-0,000 (0,131)	0,238** (0,110)	0,056 (0,107)	-0,038 (0,120)	0,218** (0,105)	0,110 (0,081)
Diferencia del número de computadoras t vs t+k	0,034 (0,129)	0,135 (0,123)	0,031 (0,118)	-0,003 (0,072)	0,031 (0,070)	-0,012 (0,113)	0,022 (0,071)	0,016 (0,060)
Porcentaje de computadoras para la enseñanza	-0,283 (2,955)	0,065 (2,940)	2,614 (2,692)	0,305 (1,929)	0,380 (1,861)	0,796 (2,520)	-0,389 (1,848)	-2,728* (1,526)
Porcentaje aulas en buenas condiciones	2,200 (2,269)	-3,242+ (2,223)	-1,777 (2,118)	-0,131 (1,719)	1,597 (1,671)	1,618 (1,995)	-0,380 (1,669)	2,727* (1,474)
Número de ambientes = 0						-0,123 (2,883)	1,779 (2,621)	0,000 (0,000)
Número de ambientes = 1	1,972 (2,724)	-1,531 (2,628)	1,327 (2,479)	1,333 (1,980)	0,697 (1,898)	-0,290 (2,322)	1,841 (2,303)	0,169 (1,271)
Número de ambientes = 2	2,007 (2,671)	0,254 (2,592)	1,807 (2,446)	0,984 (1,909)	0,922 (1,845)	0,853 (2,214)	2,025 (2,179)	0,623 (1,397)
Número de ambientes = 3	4,247+ (2,868)	2,547 (2,777)	3,634 (2,636)	-1,407 (2,066)	-1,192 (1,987)	2,143 (2,278)	0,122 (2,215)	-1,189 (1,789)
Número de ambientes = 4	1,510 (3,428)	-0,968 (3,300)	5,215+ (3,173)	-2,268 (2,794)	-3,792 (2,714)			
Altitud de la II.EE	0,003 (0,002)	0,001 (0,002)	0,004+ (0,002)	-0,000 (0,002)	0,003+ (0,002)	0,002 (0,002)	-0,002 (0,002)	0,003* (0,002)
Altitud de la II.EE al cuadrado	-0,000* (0,000)	-0,000 (0,000)	-0,000* (0,000)	-0,000 (0,000)	-0,000+ (0,000)	-0,000* (0,000)	0,000 (0,000)	-0,000+ (0,000)
II.EE Polidocente	-0,277 (3,957)	-0,840 (4,148)	6,211* (3,377)	1,424 (2,720)	4,051+ (2,520)	-0,319 (3,158)	0,287 (2,619)	1,659 (2,272)
II.EE Pública	-1,207 (2,217)	-3,872* (2,149)	-4,342** (2,058)	1,019 (1,655)	-1,875 (1,609)	-1,586 (1,858)	1,422 (1,542)	-2,973* (1,640)
Brecha de pobreza total	-0,007 (0,171)	-0,365** (0,165)	-0,091 (0,155)	-0,191+ (0,127)	-0,067 (0,121)	-0,030 (0,153)	-0,273** (0,123)	-0,088 (0,111)
Coeficiente de Gini	-36,233 (27,193)	19,125 (27,251)	-47,975* (25,219)	50,669** (20,862)	26,239 (19,844)	-26,457 (23,769)	57,660*** (20,002)	11,762 (16,901)
Gasto per capita a precios de Lima Metropolitana	-0,010 (0,014)	-0,047*** (0,013)	-0,012 (0,013)	-0,027** (0,011)	-0,013 (0,011)	-0,017 (0,012)	-0,037*** (0,011)	-0,003 (0,010)
Porcentaje población sin agua ni desagüe de red pública	-8,231 (25,225)	3,548 (25,534)	-19,279 (23,688)	-17,256 (18,447)	-16,498 (17,408)	-1,265 (21,858)	-30,188* (18,025)	-28,303* (15,050)
Porcentaje población sin alumbrado eléctrico	31,631 (25,147)	-28,686 (26,304)	42,811* (24,358)	9,869 (19,656)	20,401 (18,248)	17,013 (22,127)	18,322 (19,236)	13,977 (16,325)
Porcentaje población sin servicio de información ni comunicación	13,031 (25,356)	-12,616 (24,598)	-20,767 (23,761)	3,103 (18,075)	-14,194 (17,459)	9,505 (22,284)	7,471 (17,844)	0,766 (15,821)
Porcentaje población analfabeta	3,066 (31,474)	-27,002 (31,354)	-36,833 (29,748)	-39,334+ (24,511)	-36,138+ (23,464)	8,553 (27,582)	-25,779 (24,078)	-34,756* (20,064)
Promedio de años de edad del distrito	-0,274 (0,432)	0,721* (0,432)	-0,173 (0,403)	0,419 (0,337)	0,261 (0,318)	-0,073 (0,384)	0,666** (0,329)	0,173 (0,295)
Porcentaje de población rural del distrito	-12,073** (5,274)	-1,608 (5,336)	-4,679 (4,942)	-2,245 (3,838)	-0,326 (3,652)	-11,011** (4,582)	-3,487 (3,769)	1,683 (3,264)
Población del distrito	0,000 (0,000)	-0,000 (0,000)	0,000 (0,000)	-0,000 (0,000)	0,000 (0,000)	-0,000 (0,000)	-0,000 (0,000)	0,000 (0,000)
Tasa de crecimiento poblacional intercensal del distrito	-5,014** (2,002)	-1,150 (2,025)	-2,972+ (1,885)	0,068 (1,645)	1,200 (1,514)	-4,074** (1,755)	1,175 (1,551)	-0,543 (1,335)
Tasa de crecimiento de la población rural intercensal del distrito	0,469 (0,757)	0,036 (0,731)	0,700 (0,703)	-1,086+ (0,665)	-0,376 (0,642)	0,448 (0,550)	-0,668 (0,503)	0,886+ (0,588)
Constante	36,204** (15,860)	19,441 (15,866)	29,410** (14,797)	-4,784 (11,881)	-6,961 (11,536)	29,047** (14,119)	-9,497 (11,907)	-13,543 (10,662)
Observaciones	826	804	840	1,063	1,079	1,098	1,219	1,588

Errores estándar en paréntesis

**** p<0.01, ** p<0.05, * p<0.1, + p<0.15*

ANNEX 8:

VARIABLES	Modelo 1 Acceso a banda ancha en el t=2010 Comprensión de textos	Modelo 1 Acceso a banda ancha en el t=2010 Lógico-matemática	Modelo 2 Acceso a banda ancha en el t=2010 dado que no tenía internet en el t- Comprensión de textos	Modelo 2 Acceso a banda ancha en el t=2010 dado que no tenía internet en el t- Lógico-matemática
Acceso a la Internet de alta velocidad	0,178	-2,135	6,866	-2,756
	(3,467)	(3,052)	(4,842)	(4,274)
Promedio de alumnos de 2 grado por aula	0,224***	0,092	0,226***	0,094
	(0,076)	(0,067)	(0,077)	(0,068)
Acceso a agua potable	-1,693	-1,705	-1,620	-1,701
	(1,630)	(1,435)	(1,633)	(1,441)
Acceso a desague	6,152**	2,512	6,089**	2,591
	(2,500)	(2,201)	(2,518)	(2,223)
Total de aulas	0,193**	-0,006	0,193**	-0,014
	(0,094)	(0,083)	(0,095)	(0,084)
Total de computadoras por aula	0,244**	0,052	0,244**	0,056
	(0,103)	(0,090)	(0,104)	(0,091)
Diferencia del número de computadoras t vs t+k	-0,038	-0,022	-0,044	-0,029
	(0,068)	(0,060)	(0,069)	(0,061)
Porcentaje de computadoras para la enseñanza	-4,531***	-0,941	-4,397***	-0,854
	(1,693)	(1,490)	(1,702)	(1,503)
Porcentaje aulas en buenas condiciones	2,770*	1,862+	2,771*	1,843+
	(1,420)	(1,250)	(1,430)	(1,263)
Número de ambientes = 0	0,000	0,000	3,065+	0,421
	(0,000)	(0,000)	(2,101)	(1,855)
Número de ambientes = 1	0,051	0,466	3,223+	1,008
	(1,311)	(1,155)	(1,995)	(1,761)
Número de ambientes = 2	-0,629	-0,089	2,469	0,227
	(1,488)	(1,310)	(2,006)	(1,771)
Número de ambientes = 3	-3,160+	-0,632	0,000	0,000
	(2,078)	(1,829)	(0,000)	(0,000)
Altitud de la II.EE	0,004**	0,001	0,005***	0,001
	(0,002)	(0,002)	(0,002)	(0,002)
Altitud de la II.EE al cuadrado	-0,000**	-0,000	-0,000**	-0,000
	(0,000)	(0,000)	(0,000)	(0,000)
Brecha de pobreza total	-0,049	-0,113	-0,049	-0,106
	(0,137)	(0,120)	(0,137)	(0,121)
Coeficiente de Gini	3,419	-9,173	3,201	-10,014
	(18,802)	(16,552)	(18,888)	(16,675)
Gasto per capita a precios de Lima Metropolitana	-0,002	-0,005	-0,002	-0,005
	(0,011)	(0,010)	(0,011)	(0,010)
Porcentaje población sin agua ni desagüe de red pública	2,862	-17,435	2,767	-17,418
	(17,450)	(15,362)	(17,505)	(15,454)
Porcentaje población sin alumbrado eléctrico	20,197	17,797	23,669	17,545
	(22,347)	(19,673)	(22,456)	(19,825)
Porcentaje población sin servicio de información ni comunicación	8,303	4,607	6,555	3,361
	(17,464)	(15,374)	(17,531)	(15,477)
Porcentaje población analfabeta	-61,828**	2,607	-60,940**	4,743
	(25,043)	(22,046)	(25,097)	(22,157)
Promedio de años de edad del distrito	0,423	-0,308	0,427	-0,327
	(0,322)	(0,284)	(0,324)	(0,286)
Porcentaje de población rural del distrito	-1,855	-2,617	-2,043	-2,657
	(3,991)	(3,514)	(4,006)	(3,537)
Población del distrito	0,000	0,000	0,000	0,000
	(0,000)	(0,000)	(0,000)	(0,000)
Tasa de crecimiento poblacional intercensal del distrito	-0,387	-1,979+	-0,293	-1,958+
	(1,488)	(1,310)	(1,499)	(1,323)
Tasa de crecimiento de la población rural intercensal del distrito	0,314	-0,316	0,308	-0,300
	(0,445)	(0,392)	(0,446)	(0,394)
Constante	-22,336**	10,140	-25,562**	10,233
	(11,271)	(9,922)	(11,736)	(10,361)
Observaciones	1,276	1,276	1,261	1,261

Errores estándar en paréntesis
Nivel de significancia: ***: 0.01%, **:0.05%, *:0.1%, +:0,15

ANNEX 9:

	Grupo I vs IV+V	Grupo II vs IV+V	Grupo I vs II+III+IV +V	Grupo II vs III+IV+V	Grupo III vs IV+V
Año de acceso t=	**2008**	**2009**	**2008**	**2009**	**2010**
Variables					
Promedio de alumnos de 2 grado por aula	0,035***	0,013	0,031***	0,011	0,007
	(0,012)	(0,015)	(0,011)	(0,014)	(0,011)
Contaban con agua Potable en el año t-1	0,743+	0,623	0,497	0,738	
	(0,473)	(0,593)	(0,413)	(0,587)	
Contaban con Desague en el año t-1	-0,033	0,097	0,233	0,014	1,164
	(0,530)	(0,693)	(0,491)	(0,692)	(1,024)
Total de aulas en el año t-1	0,010	-0,002	-0,006	-0,004	0,023
	(0,025)	(0,027)	(0,024)	(0,026)	(0,016)
Pared de ladrillo o bloque de cemento en el año t-1	-0,300	1,017	-0,216	1,026	0,062
	(0,559)	(0,769)	(0,536)	(0,762)	(0,317)
Total de computadoras para la enseñanza en el año t-1	0,107***	0,051**	0,086***	0,046**	-0,001
	(0,022)	(0,025)	(0,018)	(0,023)	(0,013)
Cambio en el número de computadoras entre el año t-1 y t	0,061***	0,025+	0,051***	0,023+	0,033***
	(0,022)	(0,016)	(0,017)	(0,016)	(0,010)
Porcentaje de computadoras para la enseñanza en t-1	-1,822***	-0,701*	-1,354***	-0,665*	-0,281
	(0,536)	(0,410)	(0,471)	(0,396)	(0,243)
Porcentaje de aulas en buenas condiciones en t-1	0,036	0,593	-0,066	0,595	0,151
	(0,559)	(0,604)	(0,533)	(0,604)	(0,321)
Número de ambientes=1 Escolares en t-1	-0,130	0,059	-0,164	0,915	0,261
	(0,540)	(0,508)	(0,422)	(0,749)	(0,226)
Número de ambientes=2 Escolares en t-1	-0,339	0,283	-0,519	1,160+	0,617***
	(0,539)	(0,487)	(0,408)	(0,725)	(0,232)
Número de ambientes=3 Escolares en t-1	-0,179	0,120	-0,183	0,948	0,765***
	(0,551)	(0,513)	(0,403)	(0,722)	(0,280)
Número de ambientes=4 Escolares en t-1	0,042	-0,876			
	(0,652)				
Número de ambientes=7 Escolares en t-1			-0,126		
			(0,570)		
Número de ambientes=8 Escolares en t-1				0,824	
				(0,841)	
Altitud (msnm)	-0,000	-0,001	-0,000	-0,001	0,000
	(0,001)	(0,001)	(0,000)	(0,001)	(0,000)
Altitud (msnm)2	0,000	0,000	-0,000	0,000	-0,000
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Escuela polidocente en t-1	-0,435	0,390	-0,274	0,295	0,374+
	(0,379)	(0,382)	(0,360)	(0,377)	(0,251)
Escuela pública en t-1	-1,911***	-1,252***	-1,360***	-1,021***	-1,469***
	(0,417)	(0,353)	(0,378)	(0,346)	(0,250)
Brecha de pobreza total (%)	-0,219**	-0,000	-0,179**	0,005	-0,033
	(0,089)	(0,063)	(0,076)	(0,061)	(0,034)
Coeficiente de Gini	14,901**	-2,048	13,519**	-1,420	-4,790
	(7,103)	(6,623)	(6,655)	(6,360)	(3,787)
Gasto per cápita precios de Lima Metropolitana	-0,006**	-0,003	-0,005**	-0,002	-0,003+
	(0,003)	(0,002)	(0,002)	(0,002)	(0,002)
Porcentaje de la población del distrito sin agua ni desagüe de red	10,471	-20,799*	6,660	-21,240*	1,399
	(8,219)	(12,474)	(7,230)	(11,828)	(4,263)
Porcentaje de la población del distrito sin alumbrado eléctrico	9,174	8,155	9,292	5,132	7,116+
	(8,978)	(9,833)	(8,255)	(9,232)	(4,663)
Porcentaje de la población del distrito in servicio de información ni comunicación	-23,256***	-14,417*	-18,314**	-12,236+	-14,648***
	(8,594)	(8,609)	(7,882)	(8,259)	(4,455)
Porcentaje de la población del distrito analfabeta	-7,577	-16,048	-12,347	-15,485	2,897
	(14,983)	(14,719)	(14,203)	(14,350)	(5,900)
Edad promedio del distrito	0,165*	0,100	0,131+	0,074	0,086
	(0,095)	(0,103)	(0,089)	(0,099)	(0,062)
Porcentaje de la población que vive en el área rural	2,517+	0,766	2,054	0,790	-1,559*
	(1,732)	(1,829)	(1,540)	(1,791)	(0,876)
Población del distrito	-0,000	-0,000	-0,000	-0,000	-0,000
	(0,000)	(0,000)	(0,000)	(0,000)	(0,000)
Tasa de crecimiento intercensal de la población	0,235	0,038	0,233	0,016	-0,052
	(0,400)	(0,445)	(0,370)	(0,427)	(0,236)
Tasa de crecimiento intercensal de la población rural	0,064	-0,014	0,055	-0,018	0,055
	(0,095)	(0,187)	(0,079)	(0,146)	(0,077)
Constante	-5,053	-3,693	-5,301+	-4,429	-2,049
	(3,566)	(3,855)	(3,398)	(3,829)	(2,330)
Observations	1.507	2.117	2.025	2.393	3.262
Pseudo R2	0,35	0,30	0,27	0,26	0,29

Errores estándar en paréntesis
Nivel de significancia: ***: 0.01%, **:0.05%, *:0.1%, +:0,15

ANNEX 10:

Results of logistic regression models-Access to broadband Internet

Variables	Modelo 1 Acceso a banda ancha en el t=2010	Modelo 2 Acceso a banda ancha en el t=2010 dado que no tenía internet en el t-1=2009
Promedio de alumnos de 2 grado por aula t-1	0,029	0,049
	(0,025)	(0,040)
Con agua en t-1	0,482	0,420
	(0,697)	(0,926)
Con desagüe en t-1	-0,560	
	(1,084)	
Total de aulas en el año t-1	0,113***	0,133***
	(0,026)	(0,040)
Pared de ladrillo o bloque de cemento	-0,270	0,556
	(0,609)	(1,111)
Total de computadoras para la enseñanza en el año t-1	0,036+	0,045
	(0,025)	(0,040)
Cambio en el número de computadoras entre el año t-1 y t	-0,018	-0,026
	(0,019)	(0,027)
Porcentaje de computadoras para la enseñanza en t-1	0,533	0,617
	(0,644)	(0,984)
Porcentaje de aulas en buenas condiciones en t-1	0,543	0,254
	(0,567)	(0,838)
Número de ambientes=0 Escolares en t-1	0,064	1,348
	(0,751)	(1,364)
Número de ambientes=1 Escolares en t-1	0,056	1,412
	(0,644)	(1,185)
Número de ambientes=2 Escolares en t-1	0,361	1,787
	(0,578)	(1,097)
Número de ambientes=3 Escolares en t-1		'-0,291
		'(1,031)
Altitud (msnm)	0,001	'0,000
	(0,001)	'(0,001)
Altitud2	-0,000	'0,000
	(0,000)	'(0,000)
Brecha de pobreza total (%)	-0,089	'-0,096
	(0,087)	'(0,111)
Coeficiente de Gini	-0,498	'-1,357
	(8,816)	'(11,832)
Gasto per cápita precios de Lima Metropolitana	-0,006	'-0,006
	(0,006)	'(0,007)
Porcentaje de la población sin agua ni desagüe de red	4,679	'11,908
	(9,135)	'(11,434)
Porcentaje de la población sin alumbrado eléctrico	3,555	'-5,658
	(10,569)	'(14,728)
Porcentaje de la población sin servicio de información ni comunicación	-24,361***	'-27,551**
	(9,299)	'(12,574)
Porcentaje de la población analfabeta	-14,196	'-8,097
	(13,395)	'(17,927)
Edad promedio del distrito	0,058	'-0,071
	(0,146)	'(0,199)
Porcentaje depersonas que vive en el área rural	4,165**	'5,072**
	(1,720)	'(2,086)
Población	0,000	'0,000
	(0,000)	'(0,000)
Tasa de crecimiento intercensal de la población	-1,002+	'-2,078*
	(0,652)	'(1,187)
Tasa de crecimiento intercensal de la población rural	-0,264	'-0,092
	(0,421)	'(0,269)
Constante	-2.640	-0,497
	(5.298)	(7,716)
Observaciones	1.592	1.496
Pseudo R2	0,2174	0,1888

Nivel de significancia: ***: 0,01%, **:0,05%, *:0,1%, +:0,15.
Errores estándar en paréntesis.
Elaboración propia.